

THE ELECTRIC CARGO CYCLE ROUTING PROBLEM:
AN ENHANCED APPROACH WITH PREDICTIVE BATTERY PERFORMANCE

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Abstract

This thesis explores the optimization of electric cargo cycles (ECCs) for urban logistics, focusing on battery performance and routing efficiency. By analyzing two ECCs under different operational scenarios, a novel Electric Cargo Cycle Battery (ECCB) model is developed for battery performance forecasting. This extends to the creation of the Electric Cargo Cycle Routing Problem (ECCRP), an adaptation of the capacitated vehicle routing problem, and its Enhanced version (E-ECCRP), incorporating battery constraints and the flexibility of battery swapping. Comparative analysis of these models reveals the benefits of integrating battery performance into routing strategies, underscoring ECCs' role in eco-friendly urban logistics. This research offers valuable insights into electric mobility utilization for sustainable city transport solutions, providing a foundation for optimizing ECC usage in urban environments.

Dedication

This thesis is dedicated to Duke, my loyal dog and best companion, who has been there in every step of this journey, offering silent support through countless days and nights of work. He has unwittingly become as familiar with the contents of this document as I am, a testament to the many conversations we've shared about my work.

I also dedicate this work to my beautiful family: my mother, Joselin; my father, Onasis; my brothers, Emmanuel, Steve, and Johan; my grandmothers, Nuris and Laura; along with my aunts, uncles, and cousins. Their faith in me and endless support have been the backbone of my endeavors, offering strength and encouragement without ever doubting my path.

And to my beloved children, John, Johan, Junnior, and Julibeth, who I have sorely missed during this time, your presence is the light of my life. This accomplishment is not just mine but ours, for you are my inspiration and motivation in all things. To all of you, thank you!

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1. Introduction

The recent growth of electric cargo cycles (ECCs) reflects advancements in battery technology and a growing interest in sustainable urban transport solutions. Cargo Bikes in Canada (2021) categorizes ECCs into diverse forms, acknowledging their potential to alleviate urban congestion and support eco-friendly delivery options. Despite their benefits, ECCs face challenges in broader adoption, attributable to factors such as cost and lack of awareness. Nonetheless, initiatives like Ontario's cargo e-bike pilot (Government of Ontario, 2021) and subsequent opt-in from cities such as Toronto reflect a positive shift toward their acceptance.

ECCs promise operational efficiency in urban deliveries, balancing eco-conscious appeal with practical constraints like load capacity and battery consumption. Their design focuses on essential components like payload capacity, motor power, and battery, directly influencing their performance and environmental impact. However, the complexity of optimizing ECCs for efficient use, especially concerning battery performance, highlights a gap in the current literature. This gap needs a deeper exploration of relationships among variables affecting ECC operation to better understand these dynamics.

This research explores the increasingly vital role of ECCs in urban logistics, responding to growing environmental concerns and the push for sustainable transportation solutions. This comprehensive study delves into various dimensions of ECC deployment, focusing on performance analysis, battery optimization, and routing problems to enhance operational efficiency in urban freight systems.

By addressing critical gaps in the literature and presenting innovative analytical models, this research paves the way for more sustainable, efficient, and effective use of ECCs in urban transportation networks.

1.1. Goals and Objectives

The main goal of this research is to identify how battery range, capacity, power, speed, consumption rate, weight, road slope, temperature, and other variables interact to improve ECC route optimization. Such insights hold substantial value for logistics companies and individual service providers specializing in pickups and deliveries in urban settings.

To fulfill this goal, the research is structured around four key objectives:

1. Conduct a comprehensive review of the literature to pinpoint all factors influencing the battery performance of ECCs,

2. Collect data on ECCs under different conditions of load capacities and assistance levels,
3. Create a model that forecasts battery usage based on different variables,
4. Develop a base ECC vehicle routing model using manufacturer specifications, and an enhanced ECC vehicle routing model using the battery model, considering configurations with one and two batteries.

1.2. Scope

The scope of this thesis falls within the previously stated goals and objectives, developing a comprehensive literature review that explores the domains of micromobility, electric bicycles (E-bikes), and ECCs. The scope is defined by the methodology outlined in Chapter 3, which includes the data collection process executed for 5 kilometres trips at the York University Keele Campus during the fall of 2023. This data collection phase was characterized by the employment of commercial devices aimed at tracking cycling activity, alongside a detailed examination of a battery model, focusing on two distinct ECCs.

The statistical analysis applied to the gathered dataset is methodically narrowed to go over aspects such as outliers, linearity, model selection and evaluation, accuracy validation, and sensitivity analysis. This analysis employs typical statistical methodologies suited for the nature of the data gathered.

Furthermore, the discourse surrounding the route optimization problem, a pivotal aspect of this study, is specifically tailored to adhere to the constraints identified in Chapter 6. The models evaluated exclude time windows, the age of the ECC batteries, and the inclusion of alternative ECCs.

The rest of the thesis is organized as follow. Chapter 1 introduces the goals, objectives and scope of the study. Chapter 2 provides an in-depth review of the existing literature, offering a critical examination of studies related to micromobility, ECCs, battery technology, and logistics optimization. It highlights the gaps in current research, particularly around ECC performance metrics, battery optimization, and route optimization.

Chapter 3 details the methodology employed in evaluating ECC performance, focusing on two specific ECCs, the Ami Trishaw and the Babboe Pro Trike. This section outlines the experimental framework, the methodology for data collection, and the statistical instruments utilized for data analysis. It introduces a variety of algorithms such as polynomial regression, random forest, and neural network. Additionally, it discusses the criteria for developing various route optimization models, essential for applying the aforementioned algorithms to achieve tangible outcomes.

Chapter 4 delves into the data analysis, presenting a comprehensive examination of the performance characteristics of Ami and Babboe. It explores the impact of assistance levels, extra weight, total weight, and distance on battery efficiency, employing a blend of linear and non-linear statistical methods to understand the complex dynamics at play.

Chapter 5 introduces the Electric Cargo Cycle Battery (ECCB) Model, a pioneering approach to predicting battery performance in real-world scenarios. Through testing and comparison of various statistical and machine learning models, the chapter identifies the most accurate methods for forecasting the state of charge (SoC), highlighting the importance of reliable predictions in optimizing ECC operations. This model not only enhances understanding of ECC battery dynamics but also lays the groundwork for more effective deployment strategies in urban logistics.

Chapter 6 focuses on the Electric Cargo Cycle Routing Problem (ECCRP), a variation of the Capacitated Vehicle Routing Problem (CVRP) tailored to the unique constraints of ECCs. By integrating battery capacity considerations into routing decisions, this model advances the field of logistics optimization, offering a more nuanced approach to planning ECC deployments. Through a series of optimization scenarios, the study compares different routing strategies, highlighting the benefits of incorporating the ECCB model into the routing problem to achieve greater operational efficiency.

2. Literature Review

This chapter deeps dive into the realm of micromobility, a burgeoning sector of urban transportation that promises to reshape how we navigate densely populated areas. At the heart of this exploration are Electric Cargo Cycles (ECCs), innovative vehicles that stand at the intersection of technology, sustainability, and urban logistics. As cities worldwide struggle with the dual challenges of congestion and carbon emissions, ECCs emerge as a compelling solution, offering a greener alternative to traditional motorized transport for the delivery of goods and services.

This chapter traces the concept of micromobility, from its inception to its current status as a key player in the future of urban mobility. Special attention is paid to ECCs, exploring their technological advancements, and the pivotal role they play in forging more sustainable and efficient urban transportation networks.

The narrative extends beyond a mere overview of ECCs, delving into the details of their design, the critical role of battery technology, and the factors that influence their performance. From payload capacity and power output to the challenges posed by environmental conditions and operational efficiency, this chapter aims to provide a comprehensive understanding of ECCs and their potential to revolutionize urban logistics.

Furthermore, the introduction lays the groundwork for an in-depth discussion on the adoption of ECCs, addressing both the opportunities they present and the obstacles that hinder their widespread uptake. It explores the impact of e-commerce on urban delivery systems and the strategic role ECCs can assume within this context. Potential solutions to facilitate ECC adoption are shown, highlighting the importance of supportive regulatory measures, public authority initiatives, and infrastructure enhancements.

Innovative approaches to data collection and modelling strategies for optimizing ECC operations are referenced, underscoring the need for further research to fully harness the potential of ECCs in urban environments. By identifying different variables such as assistance level, battery range, and energy consumption and their relationship with route optimization models based on the literature, this chapter seeks to recognize the boundaries of current methodologies and pave the way for more efficient and sustainable urban delivery systems.

2.1. Micromobility

Micromobility was popularized in the urban lexicon for transportation in 2016 by Horace Dediu, an American industry analyst and investor. He described micromobility as "minimal mobility and

thus human-scale mobility," setting a maximum vehicle weight limit of "no more than five times its anticipated human payload, or 500 kg" (Dediu, 2019). The International Transport Forum (ITF) expanded the definition of micromobility by introducing parameters such as a maximum speed of 45 km/h and a weight limit of 350 kg (ITF, 2020).

Micromobility vehicles, presented in Table 1, are devices used for micromobility, are solely human-powered vehicles for individual use or small cargo transport in urban settings (ITF, 2020). Although humans have engaged with conventional bicycles, kick scooters, powered standing scooters, and powered skates for over a century (United States Patent No. US1192514A, 1916; Scientific American, 1906) the micromobility paradigm presents a fresh perspective on categorizing them. The concept bridges the divide between standard motorized vehicles and pedestrians, providing efficient alternatives for short to medium-length commutes.

Table 1 Micromobility Vehicle Types
Adapted from ITF (2020)

Micromobility Vehicle	Power	Wheels	Pedals	Control
Motor Scooter	Petrol or Electric	2-3	No	Handlebars
Powered Two-Wheeler	Petrol or Electric	2	No	Handlebars
Moped	Petrol or Electric	2-3	Optional	Handlebars
Bicycle	Human	2+	Yes	Handlebars
e-bike	Electric	2+	Yes	Handlebars
Pedal Assisted Bicycle	Electric	2+	Yes	Handlebars
Pedelec	Electric	2+	Yes	Handlebars
Speed-Pedelec	Electric	2+	Yes	Handlebars
Mobility Scooter	Electric	3-4	No	Handlebars
Standing Scooter	Human	2-4	No	Handlebars
e-scooter	Electric	2-4	No	Handlebars
Skateboard	Human	4	No	Feet
Electric Skateboard	Electric	4	No	Remote
Hoverboard	Electric	2	No	Leaning
One-wheel	Electric	1	No	Leaning
Electric Unicycle	Electric	1	No	Leaning
Electric Skates	Electric	2	No	Leaning or Remote
Skates	Human	2	No	Feet

Table 1 showcases a diverse range of vehicles, varying from those with a single wheel to those with four wheels, though most commonly featuring two or three wheels. The primary mode of propulsion for the majority is electric power, with a minority powered by petrol or human effort. Only the models related to bicycles are equipped with pedals. In contrast, most other vehicles are maneuvered using handlebars. However, certain types, like skateboards and skates, are

propelled by the user's feet, while some are controlled remotely or by the user's body movements, such as leaning.

Distinctive functionalities include a supportive power unit for E-bikes, with Pedal Assisted Bicycles offering assistance only during pedaling. Pedelec vehicles automatically disengage assistance at speeds around 25 km/h. Mobility scooters are specifically designed for individuals with mobility restrictions, and the range of vehicles from Hoverboards to Electric Skates feature self-balancing technology.

Given the increasing market of micromobility vehicles as shown in sections 2.1.1 and 2.1.2, there is a need for diversified classification systems. These systems depend on multiple factors, such as the unique regulatory frameworks for each jurisdiction. Different countries and regions have their own systems for categorizing micromobility vehicles based primarily on speed and weight with potential consideration for other parameters as shown in Table 2.

Table 2: Micromobility Vehicles Categories

Category	Type	Description	Suitability	Common Use	Reference
Propulsion	Human-powered	Vehicles operated solely by human effort	Short-distance, exercise	Traditional bikes, push scooters	(National Association of City Transportation Officials (NACTO), 2009)
	Electric-powered	Vehicles powered by electric motors	Medium distance, urban commuting	e-bikes, e-scooters, e-Cargo bikes	(International Transport Forum (ITF), 2020)
	Hybrid	Vehicles with both human and electric propulsion	Variable distances, versatile use	Certain modern e-bikes	(National Association of City Transportation Officials (NACTO), 2017)
Configuration	Single-track	Vehicles with one line of wheels	Individual use, narrow paths	Bicycles, e-bikes, unicycles	(MassDOT, 2015)
	Multi-track	Vehicles with more than one line of wheels	Cargo transport, stability	Tricycles, quadricycles, cargo bikes	(MassDOT, 2015)
Intended Use	Personal Mobility	Vehicles primarily for individual transport	Daily commuting, recreation	e-bikes, e-scooters, personal cargo bikes	(International Transport Forum (ITF), 2020)
	Cargo Transport	Vehicles designed to carry goods or cargo	Deliveries, shopping, transporting kids	Cargo bikes, e-Cargo bikes	(European Cycle Logistics Federation, 2023)
	Recreational	Vehicles primarily for fun or sport	Leisure, off-road activities	Hoverboards, electric skateboards	(National Association of City Transportation Officials (NACTO), 2009)
	Special Purpose	Vehicles designed for specific needs or groups	Adapted mobility, tandem riding	Adaptive bikes, tandem bikes	(World Health Organization (WHO), 2023)

Category	Type	Description	Suitability	Common Use	Reference
Capacity	Light	Vehicles designed for minimal load beyond the rider	Individual commuting	e-bikes, e-scooters	(National Association of City Transportation Officials (NACTO), 2009)
	Medium	Vehicles with some cargo capacity	Grocery shopping, kid transport	Personal cargo bikes	(European Cycle Logistics Federation, 2023)
	Heavy	Vehicles with significant cargo capacity	Commercial deliveries, heavy loads	e-Cargo bikes, tricycles	(European Cycle Logistics Federation, 2023)
Infrastructure	On-road	Vehicles best suited for road use	Urban and suburban commuting	e-bikes, cargo bikes, e-scooters	(National Association of City Transportation Officials (NACTO), 2009)
	Off-road	Vehicles designed for rough terrains	Adventure, mountain areas	Mountain e-bikes	(International Mountain Bicycling Association)
	Pedestrian Areas	Vehicles compatible with sidewalks or pedestrian zones	Short commutes, campus use	e-scooters, hoverboards	(International Transport Forum (ITF), 2020)
	Dedicated Tracks	Vehicles best for bike lanes or paths	Urban commuting, safe pathways	Bicycles, e-bikes, certain cargo bikes	(National Association of City Transportation Officials (NACTO), 2009)
Ownership	Privately Owned	Vehicles owned by individuals	Personal commuting, recreation	Personal e-bikes, cargo bikes	(National Association of City Transportation Officials (NACTO), 2009)
	Shared Mobility	Vehicles provided by sharing platforms	Urban commuting, tourists	Bike-sharing, e-Scooter rentals	(International Transport Forum (ITF), 2020)
	Commercial	Vehicles owned by businesses for specific uses	Deliveries, service providers	e-Cargo bikes for deliveries	(European Cycle Logistics Federation, 2023)

Table 2 shows the wide range of institutions and organizations involved with micromobility vehicles, with a significant focus on bicycles, e-bikes, and e-cargo bikes, which are subject to the most regulations among the various categories. European bodies like the European Cycle Logistics Federation concentrate on the commercial aspects of these vehicles. In contrast, NACTO primarily addresses their personal and leisure applications. The WHO is concerned with accessibility issues or the use of micro-vehicles for special purposes, whereas the ITF focuses on pedestrian concerns. All these entities engage with at least one classification system, reflecting the complexity of categorizing micromobility vehicles since a single vehicle can fall into multiple classification systems based on the criteria applied. E-bikes appear in 8 out of the 19 types listed in the table, making them the most prevalent category, followed by cargo or e-cargo bikes, across different classification systems.

2.1.1. Global Micromobility Overview

The evolution of the micromobility market over recent decades has been influenced by factors such as urbanization trends, shifts in consumer preferences, and technological advancements. The introduction of the lithium-ion battery in 1991, enabled the development of portable electric power sources suitable for the proliferation of electric micromobility vehicles (ITF, 2020). This technological advancement has led to significant growth of e-bikes and dominate the market due to their diverse options, advanced technology, extended longevity, and rapid charging capabilities (Global Market Insights, 2023; Global Research Consulting, 2022; Mordor Intelligence, 2022; Grand View Research, 2021; Santucci et al., 2016).

The market expansion for micromobility has expanded faster in Asia, which accounted for a 68% share of global revenue in 2022, representing approximately 19,900 million USD (Statista, 2022). Following Asia, Europe holds a significant market share at 29%, while North America, lags behind with a 3% global share (Statista, 2022). For example, in 2021, e-bike sales in the U.S. reached approximately 880,000 units, 2.7×10^{-3} per capita (Zachos, 2023). Conversely, despite having a smaller population, Germany saw 2 million e-bike purchases, for a rate of 2.4×10^{-2} per capita (E-Bike News, 2022).

The e-bike market is the dominated by Pedelects, which constituted over 95% of the sales in countries like Germany by 2011 (Winslott Hiselius & Svensson, 2017) and continue to be the leading segment globally recently in 2022 (Mordor Intelligence, 2022).

The economic advantages of micromobility vehicles can be substantial with potential operational cost reductions of 45% compared to standard cars (Gruber et al., 2014). This economic efficiency is a critical factor in consumer preference for more sustainable transportation options. However, factors such as purchase price and electric range remain crucial in consumer decision-making, with a significant portion of expenses attributed to batteries (Narayanan & Antoniou, 2022).

As cities worldwide adopt sustainable mobility initiatives and reconfigure urban spaces, micromobility vehicles are increasingly favored for their low environmental impact and suitability for contemporary urban environments (Serrano-Hernandez et al., 2021).

In Canada, the local market is showing a rising inclination towards sustainable and efficient urban transit solutions, presenting significant opportunities for micromobility.

2.1.2. Canadian Micromobility Overview

In Canada, a trendsetter in North America's shared micromobility landscape, Montreal has been a key player (Destinie, 2022). The first public bike-sharing system in the country dates back to

2009 in Montreal, followed by Toronto in 2014 and Vancouver in 2016 (University of British Columbia (UBC), 2020).

The Canadian Motorcycle, Bike, and Parts Manufacturing industry has seen considerable growth over the years. From 2010 to 2023, revenue increased from \$1.1 billion to \$1.5 billion, with a notable 34.6% growth before 2020. Future projections suggest a continued, albeit slower, growth trend up to 2028 (IBIS World).

Infrastructure Canada (2021) unveiled the National Active Transportation Strategy, a groundbreaking initiative to promote active transportation in cities. There is a commitment of \$400 million to enhance infrastructure like pathways, bike lanes, and trails, which are vital for micromobility projects (Infrastructure Canada, 2021).

The current usage of micromobility systems in Canada, particularly in urban centers, has shown promising trends. A 2021 Vancouver survey revealed that 16% of residents used micromobility devices to connect with public transit (HUB Cycling, 2020). This adoption rate, while already substantial, suggests considerable potential for expansion. According to Destinie (2022), the micromobility system, though already serving millions, has the capacity to support millions more as it grows and extends into new communities.

Canada's progress in micromobility, while gradual, is ongoing, with an eye towards innovative strategies in urban transportation. Through the integration of micromobility projects into both national and local transportation plans and acknowledging their contribution to urban sustainability, Canada is making strides in this evolving field.

2.2. Electric Cargo Cycles (ECCs)

The term cargo cycle describes bicycles that have been adapted to transport heavy and bulky items or passengers (Narayanan & Antoniou, 2022). Cargo cycles go back to the 19th century in Holland, used by tradesmen, milkmen, bakers, messengers (Klepfer, 2012), and were pivotal in urban transportation during the 1920s and 1930s. However, the ascent of cars, pickup trucks, and vans during the 1950s and 1960s precipitated their decline (Internationale Automobil-Ausstellung, 2019).

Recent advances in battery technology have led to the adaptation of batteries for cargo cycles, transforming them into electric cargo cycles (ECCs). This evolution has merged the two concepts, with the term ECC now commonly referring to the same type of micromobility vehicle. The interest on ECCs surpass those of traditional cargo bikes, which have become a term often used interchangeably with ECCs.

A parallel to the previously discussed micromobility vehicles can be seen in the diverse criteria used for cargo cycles. Carracedo & Mostofi (2022) segment cargo cycles by purpose, including hauling, cargo and children transport, passenger commuting, advertising, sales, tandem use, and accessibility-centric models. Cairns & Sloman (2019) classify cargo cycles into four types: conventional bikes equipped with rider pannier bags; conventional bikes with attached trailers; two-wheeled cargo bikes featuring a storage container; and three or four-wheeled cargo cycles equipped with a storage container. Gruber & Narayanan (2019) categorize cargo cycles into five segments: delivery bike, long john bike, longtail bike, front-load tricycle, and heavy-load tricycle. The organization known as Cargo Bikes in Canada (2021) classifies the 12 categories of cargo cycle by shape: box bike, box trike, child-friendly, compact, cycle truck, foldable, long John, long-tail, mid-tail, pedicab, tandem and utility bike. A depiction of these vehicle configurations is given in Figure 1.

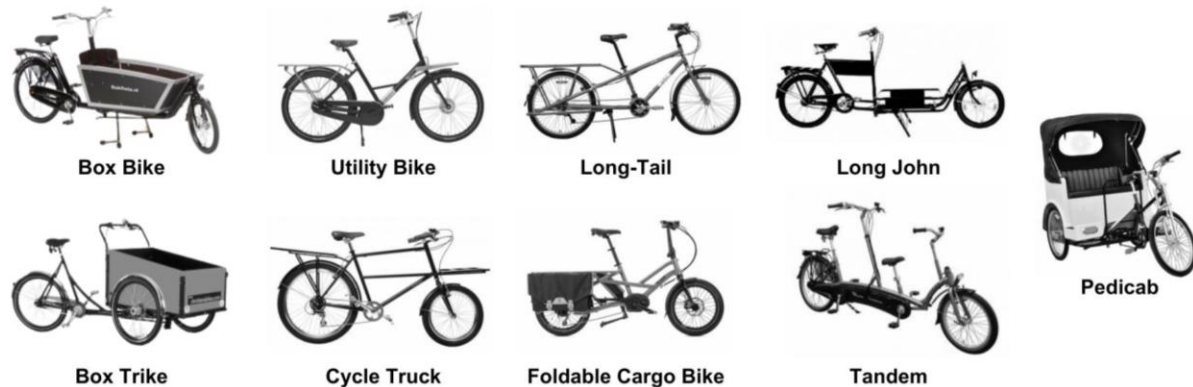


Figure 1: Cargo Bikes Categories
Adapted from Cargo Bikes in Canada (2021)

Many cargo cycles utilize electric propulsion to maintain accessibility for users as external loads are added to the vehicle. There are various classifications of e-bikes. This thesis will focus on categories broadly adopted in European and American systems. Asian countries less consistency since each country typically regulates their e-bikes under different conditions (Walker, 2019). Table 3 shows different classification systems around the world and their characteristics.

Table 3: Electric Bike Categories by Country

Country Reference	Category	Name	Max Motor Power (W)	Max Speed (km/h)	Pedal Assist	Throttle
USA (People for Bikes, 2014)	Class 1	Pedal assist e-bike (Pedelec)	750	32	x	
	Class 2	Throttle assist e-bike	750	32	x	x
	Class 3	Speed Pedelec	750	45	x	Up to 32 km/h
Canada (Government of Canada, 2020)		Power assisted Bicycles	500	32	x	
EU (Official Journal of the European Union, 2013)	L1e-A	Powered cycle	250	25	x	x
	L1e-B	Two-wheel moped	4000	45	x	
	L2e	Three-wheel moped (Passenger & Utilities)	4000	45	x	
	L6e	Light quadricycle (On-road quad, passenger & Utilities)	4000	45	x	
Australia (South Australia Police Road Safety Centre, 2021)		Power assisted pedal cycle	200	25		x
			250	25	x	Up to 6 km/h
China (Congress of the People's Republic of China, 2003)		Electric bicycle	400	15	x	x
Japan (Government of Japan, 2020)		Motorized bicycle	250	24	x	

These classification systems assist urban areas in tailoring regulations for various bike types, yet not all encompass cargo cycles in their regulatory scope. Among the systems outlined in Table 3, only the framework established by the Official Journal of the European Union (2013) includes cargo cycles in its regulations. The three-class system, recognized in the USA, excludes cargo cycles from its purview. New York is the only US state that regulates cargo cycles (Dalla Chiara et al., 2023).

2.2.1. Global ECC Overview

Cargo cycles utilizing electric assistance for propulsion are labelled in this thesis as electric cargo cycles (ECCs) have had a large surge in recent years due to technological innovations, changing consumer preferences, and increasing environmental concerns from traditional gas-powered

vehicles. ECCs are a promising solution to regions with high population density, but they have been recognized just recently (Choubassi et al., 2016) and are yet to be found as part of mobility plans in cities, especially in North America (Carracedo & Mostofi, 2022).

Last-mile delivery (LMD), the terminal phase of supply chains as products reaches the end consumers, is often marred by inefficiencies. The need to improve LMD efficiency will increase given the rise in urban dwellers in the global populace projected to increase from 56% in 2023 to 70% in 2050 (World Bank, 2023).

The International Transport Forum (ITF) projects that by 2050, delivery fleets will compete with passenger vehicles for road space and parking due to goods transport constituting up to 18% of road traffic (King, 2013). ECCs represent a way to solve this problem. The European Cyclists' Federation (2016) provides some examples illustrating this point, such as a case in Cambridge, UK, where it was found that 25% of all urban deliveries could be efficiently conducted via bicycles. This percentage rises to 50% for the delivery of light goods. Additionally, a French company successfully transported over one million packages annually using 60 cargo cycles in cities including Lyon, Bordeaux, and Paris.

Riggs (2016) conducted a survey in which 62% of the 299 respondents, primarily from the US, reported considering giving up a vehicle due to owning a cargo bike. Meanwhile, Becker & Rudolf (2018), focusing on Germany and Austria, discovered that 93% of the 931 survey participants, in collaboration with 30 Free Cargo-Bikesharing operators, concurred with the prospect of using a cargo bike in the future.

While specific numbers differ based on regions and data sources, commercial use of ECCs is limited due to factors by terminology confusion, lack of awareness about benefits, and high costs for small companies (Rudolph & Gruber, 2017). However, the industry recognizes the larger importance of ECCs in European markets, such as Germany, Denmark, France, Norway, Austria (Giglio et al., 2021; Hess & Schubert, 2019; Gruber & Kihm, 2016; Gruber et al., 2014).

By the end of 2021, ECCs sales reached 66.2% of the global cargo bike market, primarily dominated by the "Pedal Assisted" segment, which forms the largest proportion by propulsion type. Such sales are predominantly concentrated in developed countries like China, Germany, the UK, France, and the US (Mordor Intelligence, 2022).

The e-cargo/utility market reached a notable valuation of USD 1.8 billion in 2022 (Mordor Intelligence, 2022). When juxtaposed against the entire e-bike market's valuation of USD

14,404.8 million in 2022, the e-cargo sector represents a sizeable chunk, thereby indicating its growing importance within the broader e-bike ecosystem (Mordor Intelligence, 2022).

2.2.2. Canadian ECC Overview

In Canada, there is a rise in the popularity of ECCs. Data from Cargo Bikes in Canada (2023) indicates that approximately 50 companies are working with 14 different types of cargo bikes across various cities. This trend is further supported by the investment of over CAD 5.9 million by several Canadian provinces into a rebates program. This initiative aims to encourage 9,000 buyers to purchase e-bikes at lower prices (Grand View Research, 2021). The growing need for e-bikes in logistics (ECCs), especially for transporting goods, is expected to boost this market segment. Additionally, an increase in last-mile delivery and freight activities within Canada is anticipated to further propel the growth of this sector in the upcoming years (Grand View Research, 2021).

The Government of Ontario (2021) launched a cargo e-bike pilot program, granting municipalities the autonomy to decide the usage parameters for ECCs. Scheduled to operate from March 2021 through March 2026, this initiative aims to collect data from municipalities throughout the pilot period. This information will assist in deciding whether ECCs will receive permanent approval for use in Ontario and under what regulations.

The City of Toronto (2021) initiated the program in June 2021 to incorporate ECCs in last-mile deliveries. According to the report, the project will allow large ECCs to use roads, bike lanes, and cycle tracks. However, due to the pandemic and certain contractual limitations, comprehensive data on this program is not yet available.

Additional initiatives in Canada's evolving cargo bike landscape include the "Urban Quick Stop" project, a collaboration between Purolator, the University of Toronto, and the City of Toronto. The project incorporates a mini-hub shipping container to substitute traditional delivery trucks with ECCs and assess the impact on campus and the surrounding areas. The ECCs are equipped with embedded sensors to collect comprehensive data on several key areas: the reduction of emissions, enhancements in operational efficiency, changes in parking experiences, and the interactions between ECCs and other road users, including pedestrians and cyclists (Purolator Inc., 2022).

Montreal, known for its extensive history of commercial cycling, predominantly by smaller companies for delivery purposes, is also experiencing the effects of growing ECC adoption.

Purolator has introduced a fleet of ECCs in the city as part of their initiative to make their fleet more environmentally friendly (Purolator, 2021).

Lachapelle et al. (2021) developed a study focusing on occupational safety, particularly the risks of near collisions, collisions, and injuries for cyclist workers in the Montréal metropolitan area. This study involved interviewing commercial cyclists to understand task characteristics, risk-taking behaviors, and safety factors related to risks of near collisions, collisions, and injuries. Most interviewees were small company owners relying on cargo bikes, trikes, and bikes with trailers.

The study by Lachapelle et al. (2021) is among the limited research conducted on ECCs in Canada, primarily emphasizing safety details. There is a lack of comprehensive studies exploring various components of ECCs, including their integration into the urban ecosystems of Canadian cities, which cover aspects beyond safety.

Beyond these projects and studies, there is limited information on the efforts made by Canadians to incorporate ECCs into their urban and logistical frameworks. However, the direction of these initiatives suggests a positive trend towards integration.

2.2.3. Design of ECCs

The design process of ECCs encompasses a multifaceted approach to ensure that these vehicles meet the standards of efficiency, safety, and suitability for their intended purposes. The structure of ECCs typically follows the general components of e-bikes shown in Figure 2, which can vary significantly depending on the manufacturer, model, and intended use of the ECC.

However, an essential factor in designing cargo cycles is the payload capacity, which denotes the maximum total weight an ECC can transport. This includes not just the cargo, but also the rider's weight along with their clothing, riding gear, and any additional items. Presentation of this information differs across the industry, with some companies opting to list payload capacity by considering only the cargo's weight. This capacity typically ranges from 50 kg to 500 kg, as highlighted by Carracedo & Mostofi (2022). However, a significant challenge arises when trying to maximize payload capacity. Moolenburgh et al. (2020) note that prioritizing maximum payload may negatively impact the ECC's maneuverability and aesthetic appeal.

The power output of ECCs, generated by their motors, is another crucial component of the design. This power is primarily allocated for overcoming wind drag, climbing hills, compensating for bearing and tire friction (Morchin & Oman, 2006). However, there are often regulatory limits on this power output. For instance, the Senate and House of Representatives of the United States of America (2002) have set a maximum of 750 watts; the Official Journal of the European Union

(2013) has set a limit of 4,000 watts; and the Government of Canada (2020) has established a maximum of 500 watts. These regulations highlight the varying international standards for ECC power outputs as shown previously in Table 3.

Another key aspect of ECC design is the battery and subsequent range. The selection of the battery depends on several factors, including required travel distance, permissible battery weight, power needs, payload capacity, temperature, type of service, and personal preferences (Morchin & Oman, 2006). The placement of the motor and battery can vary among models, with common locations including the front and rear wheels for the motor, and the frame and rear rack for the battery (MacArthur, Dill, & Person, 2014).

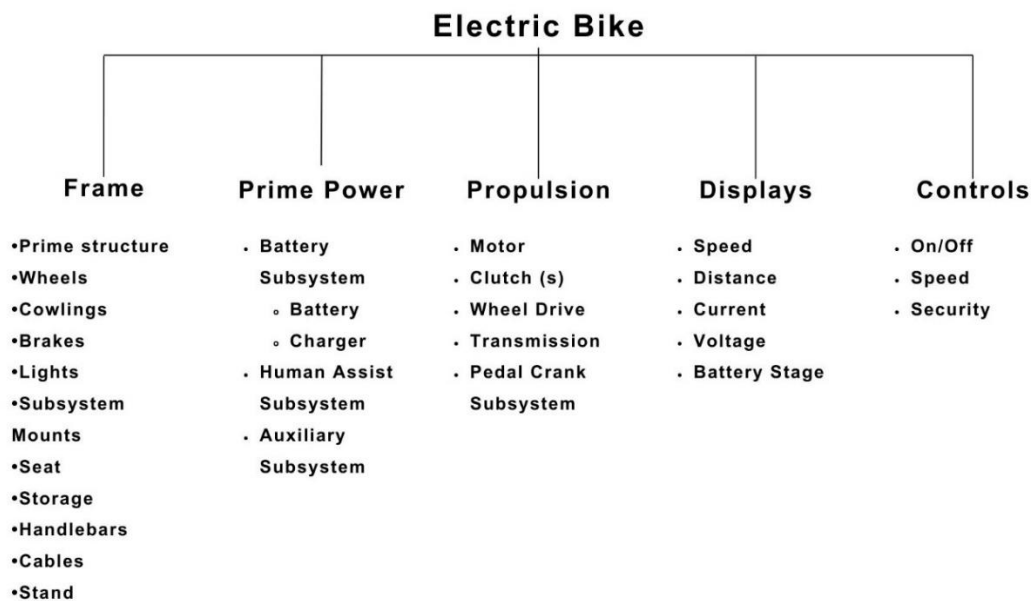


Figure 2: System Components of an Electric Bicycle
Adapted from Morchin & Oman (2006)

The material composition of each ECC system is also important when considering vehicle performance, durability, attractiveness, and environmental impact. Temporelli et al. (2022) provide a breakdown of this composition by total mass, with metals (43% aluminium, 18% steel) and polymers (18% carbon fibre, 12% plastic) forming the majority of the vehicle. Other components, including the display, engine, battery, brake pad, and electronics, contribute approximately 9% of the total mass. Despite its relatively small percentage in terms of total mass, the battery stands out as one of the most significant and environmentally impactful components of ECCs. The battery also impacts the performance and last-mile delivery strategies, making it a central focus of the research of this thesis.

2.2.4. Battery for ECCs

The role of battery technology in Electric Cargo Cycles (ECCs) is pivotal for sustainable urban logistics. In North America and Europe, ECCs commonly use lithium-ion (Li-ion) batteries, favored for their high energy density, lightweight design, and efficiency (Weiss et al., 2015; Ji et al., 2013; Liu & Chang, 2010). In contrast, lead-acid batteries are prevalent in China due to lower cost, despite their lower efficiency (Weiss et al., 2015). Alternative battery types like Nickel Metal Hydride (NiMH) and Nickel-Cadmium (Ni-Cd) are less preferred due to their charge loss when not in use and toxic components (Alpine Power Systems).

The effectiveness of batteries in ECCs is subject to a variety of influences. Factors like discharge rates, environmental temperature, charging cycles, and the aging of the battery play a significant role (Liu & Chang, 2010). For ECCs, additional elements are important such as the number of stops, frame, terrain, and the weight of the cargo also impact their operational range (Schier et al., 2016). While manufacturers generally aim for ECC ranges of 50 to 100 km, real-world performance can vary, with some ECCs achieving lower ranges from 19 to 42 km (Carracedo & Mostofi, 2022; Koning & Conway, 2016; Schier et al., 2016).

Rudolph & Gruber (2017) indicated that a battery range of 50-80 km is usually adequate for daily operations without recharging. However, opting for batteries with higher capacities can compromise the payload capacity of the vehicle, as the size and weight of the battery must be taken into account (Aiello et al., 2021; MacArthur et al., 2014). The choice of battery type is not only crucial for operational efficiency but also has a significant impact on the environmental footprint of the vehicle. For instance, the production of a lead-acid battery for an e-bike in China consumes about 8 kWh of energy, which is equivalent to the energy used in manufacturing the e-bike itself (7.1 kWh) and is enough for approximately 15,000 km of e-bike operation (Weiss et al., 2015).

ECCs are highly energy-efficient, with energy consumption ranging between 9 to 20 Wh/km (Koning & Conway, 2016; Nocerino et al., 2016; Ormond Junior et al., 2019b; Astegiano et al., 2019; Lajos Sárdi & Bóna, 2018; Tipagornwong & Figliozzi, 2014). This rate is just a tenth of the energy consumed by small electric cars and e-vans, and only 0.025% of what e-trucks use (Astegiano et al., 2019; Nocerino et al., 2016; Lajos Sárdi & Bóna, 2018).

Even though there are no certified standard tests for measuring the energy consumption rates of e-bikes and similar light vehicles (Weiss et al., 2020), it is known that charging a battery not only demands electricity but generates CO₂.

Sheth et al. (2019) found that replacing 10% of delivery vans with electric cargo bicycles could enhance network efficiency and significantly cut down on both lifecycle CO₂ and external costs associated with transportation. Schünemann et al. (2022) observed that replacing diesel delivery vans with ECCs can reduce CO₂ emissions by up to 73%.

Addressing the environmental concerns associated with the production, charging, and disposal of batteries in BEVs involves several strategies. Firstly, from a production standpoint, reducing reliance on coal for electricity generation can lessen the impact of BEVs on freshwater eutrophication and ecotoxicity, as noted by European Environment Agency (2018). For the charging process, a key method to minimize greenhouse gas (GHG) emissions includes powering charging stations with renewable energy sources, particularly during peak demand periods, and opting for less powerful charging points. In terms of disposal, sustainable practices such as reusing, recycling, and remanufacturing batteries present viable solutions to mitigate environmental impacts. These approaches collectively contribute to a more environmentally responsible lifecycle for BEVs (European Environment Agency, 2018).

Reusing batteries can be advantageous, particularly when they retain capacity due to early vehicle failures, accidents, or mismatches in lifespan expectations. However, the European Environment Agency (2018) points out that research on the impacts of reusing batteries is limited by a lack of data. Recycling batteries appears to be a viable option but is complicated by the absence of standardization in the process. On the other hand, battery remanufacturing is a newer method and is regarded as the most eco-friendly disposal solution. Despite these options, the potential for recycling, reusing, and remanufacturing batteries is currently considered low. This is attributed to various challenges, such as the limited volume of batteries reaching end-of-life (for instance, recycling 200,000 batteries could take over a decade), insufficient knowledge about battery design, and a lack of proper labeling on battery packs and cells, as reported by the European Environment Agency in 2018.

Optimizing the battery capacity can help reduce the impacts it will have during the use phase. However, this optimization can also increase the number of charging cycles required, which in turn may raise the overall cost of the battery. Usama et al. (2019) highlight that battery capacity significantly influences the routing plan of BEVs. Given the limited information available, it can be inferred that e-bikes and other micromobility vehicles follow a similar pattern. Conversely, the routing plan can also affect the battery's capacity, particularly as it degrades over time due to the wear and tear from charging and discharging. This interplay between battery capacity and vehicle operation demonstrates the complexity of maximizing the efficiency and sustainability of BEVs.

2.3. Urban Logistics

Urban logistics is a critical component of modern cities undergoing transformative changes with micromobility. ECCs offer an efficient, sustainable, and cost-effective solution for navigating the complexities of urban delivery systems (Aiello et al., 2021). They are particularly suitable for short-distance trips and small deliveries, which are common in urban settings (Moolenburgh et al., 2020; Gruber et al., 2014).

E-commerce has seen remarkable growth, significantly affecting urban logistics. In 2022, the worldwide e-commerce sector was valued at USD 5.7 trillion, with a projected growth of 20.8% for 2023 (Baluch, 2023). Within Canada, more than 27 million individuals engaged in e-commerce activities that year, representing 75% of the nation's populace. This figure is anticipated to rise to 77.6% by 2025 (International Trade Administration, 2023). This growth led to the utilization of various distribution channels, each catering to the varying needs of consumers and the logistical challenges of urban areas (Siegfried et al., 2021; Shahmohammadi, et al., 2020).

The delivery of products after reaching a Distribution Centre (DC) is shown in Figure 3. This particular last-mile phase is where ECCs are most effectively used for goods delivery. Four key distribution channels for the last-mile delivery include traditional retail, store delivery, home delivery, and pick up. Traditional retail is also known as brick-and-mortar, wherein goods are delivered to physical stores for customers to purchase and pick up the order. By contrast, the store delivery channel, sometimes known as bricks-and-clicks, encompasses deliveries that are purchased in person or ordered online to be delivered from physical stores to the end user. The third channel known as home delivery is often used for e-commerce transactions, with orders processed by a distribution centre before arriving directly to the end user. The final channel represents a pick-up option where online orders are picked up by customers from predetermined depots, such as grocery store parking lots.

The locker collection point identified for the pick up channel in Figure 3 is also sometimes known as Urban Consolidation Centres (UCCs) (Allen et al., 2012; Browne & Ryan, 2011) and Urban Micro-Consolidation Centres (UMC) (Rudolph et al., 2022). Such infrastructures operates in “two-tier” distribution schemes, which are recommended for city logistics that rely on electric vehicles (EVs) (Crainic et al., 2004). This system typically involves extra-urban Central Distribution Centres (CDCs) located on the outskirts of urban areas for the initial consolidation of goods. A second set of infrastructures, situated inside the city, facilitates the last-mile distribution (Aurambout et al., 2019; Morganti et al., 2014).

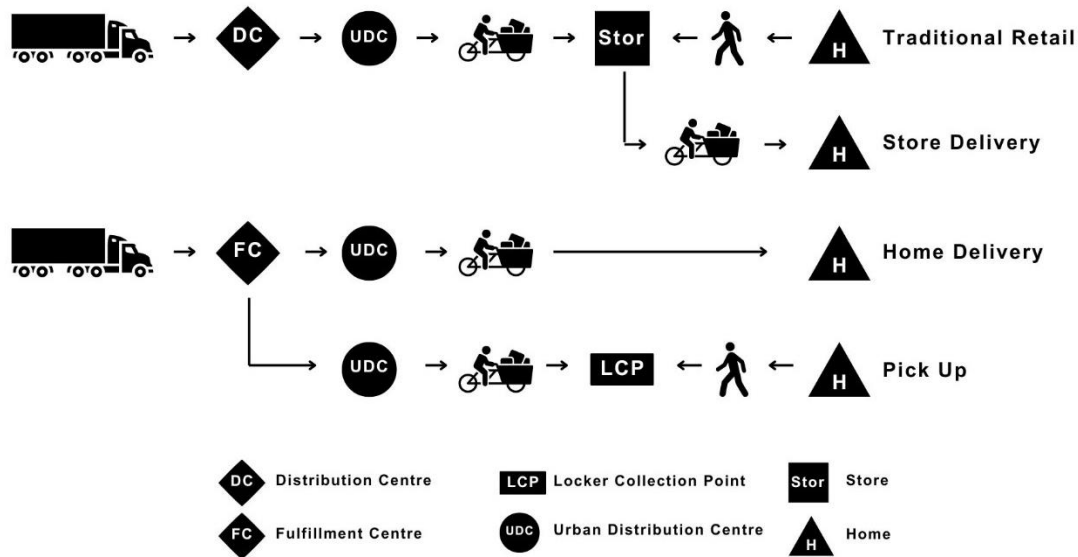


Figure 3: Distribution Channels for E-Commerce
Adapted from MetroFreight Consortium

The courier market is primarily characterized by short-distance trips. For instance, in Berlin, the average distance for bicycle deliveries is 5.1 km, whereas it is 11.3 km for car deliveries (Gruber et al., 2014). A significant majority (91%) of couriers utilize their own vehicles. This includes all bike couriers who own their bicycles, while only 88% of car couriers own their vehicles.

Gruber et al. (2014) reported that 83% of pickups and 77% of drop-offs take place in urban areas, with two-thirds of these shipment interactions occurring within the inner city. This is the case for 8 German cities, including Berlin, Hamburg and Munich. In Italian urban areas, commercial vehicles typically operate with a filling rate ranging from 20% to 40%, according to studies by the Ministero Delle Infrastrutture e dei Trasporti (2020) and Letnik et al. (2018). This underutilization of capacity makes it feasible for smaller ECCs to provide equivalent services for a typical daily distance and the payload capacity (Temporelli et al., 2022).

These considerations take more relevance when considering same-day deliveries (SDD), which reflects the urgent demand for rapid delivery services in the e-commerce era (Rajendran & Harper, 2021; Aiello et al., 2021). ECCs stand out as a viable solution to meet this demand, thanks to their seamless integration into the logistics ecosystem. Retailers are increasingly incorporating SDD services to meet consumer expectations, with a strong preference among consumers for retailers who can offer quick delivery options. Currently, about 51% of retailers provide SDD services, and this figure is expected to rise to 65% in the near future. The criticality of SDD is

further underscored by consumer behavior; a striking 75% of consumers are likely to avoid retailers that fail to deliver products swiftly (Rajendran & Harper, 2021; Brusch & Stüber, 2014).

Lenz & Riehle (2013) estimate that up to a quarter of freight transport in city centers could be efficiently managed using cargo cycles. This presents a significant opportunity for integration into existing logistics operator fleets. Although alternative fuels and vehicles, including ECCs, present an appealing prospect, their effectiveness as a mainstream urban freight strategy, especially in the U.S., is considered limited (Giuliano et al., 2013).

2.3.1. Factors of ECC Adoption

Table 4 outlines the advantages and disadvantages of ECCs across different aspects. Operational efficiency refers to how effectively ECCs are integrated into logistic operations. Economic performance involves analyzing the cost-effectiveness of ECCs, while the socio-economic aspect refers to the broader implications on society and local economies. The infrastructure and urban context category consider the compatibility of city layouts with ECC usage. Technical performance focuses on the design and capabilities of ECCs. Safety encompasses both the physical safety of ECC operators and other users. Lastly, the environmental impacts of ECCs.

Lenz and Riehle (2013) found that among 38 operators across various European countries, at least 11 could integrate ECCs into their fleets with minimal difficulties. Furthermore, direct courier trips could see between 66% and 83% of their deliveries conducted via ECC, when considering distance, weight, and volume parameters (Gruber et al., 2013). Understanding the factors that drive the adoption of ECCs is crucial as they shift from niche markets to mainstream usage. The purchase price and electric range of ECCs are pivotal considerations, with a notable trade-off between these factors since batteries constitute a significant part of the purchase cost (Gruber et al., 2014; Gruber & Kihm, 2016). Demographic factors such as age, income, and education level inversely affect the willingness to use ECCs, particularly among couriers, with males showing more inclination towards ECCs than their female counterparts (Gruber et al., 2014; Gruber & Kihm, 2016). While interest in technology and innovation affects purchase intentions, it doesn't significantly influence the actual purchase decision (Narayanan et al., 2022).

Alternative fuels and vehicles such as ECCs present an appealing prospect for urban deliveries, but their effectiveness as a mainstream freight strategy in the U.S. is considered limited (Giuliano et al., 2013). The rise of the on-demand economy has transformed delivery dynamics as consumer preferences trend towards faster deliveries (Moolenburgh et al., 2020). This shift towards faster delivery services has increased the demand for urban logistics space,

consequently driving logistics real estate to areas outside of city centers and contributing to a rise in the number of delivery vans. In response, medium-sized cities are making adjustments, focusing on creating pedestrian-friendly areas and implementing vehicle-access controls among other solutions. ECCs can complement these implementations to improve safety and supply part of the demand.

Table 4: Advantages and Disadvantages of ECCs for Urban Logistics

Operational Efficiency	Reference
Advantages Can maneuver through congested city streets faster than traditional delivery vehicles. Can access pedestrian zones, low emission zones, and other restricted areas where regular vehicles might be prohibited. Easier to park in dense urban areas, reducing the time needed for delivery drop-offs. Enhanced suitability for last-mile deliveries, which are often inefficient for larger vehicles.	Gruber et al., 2014; MacArthur et al., 2014. Serrano-Hernandez et al., 2021; Heinrich et al., 2016. Narayanan & Antoniou, 2022.; Naumov & Starczewski, 2018. Caggiani et al., 2021; Rajendran & Harper, 2021
Disadvantages Have a limitation in terms of weight and volume compared to larger vehicles. Existing supply chain and delivery systems may need adjustments to accommodate the unique operational characteristics of ECCs. Operations can be influenced by adverse weather conditions, potentially making deliveries slower or more challenging during inclement weather. More ECCs are required to substitute one van.	Moolenburgh et al., 2020; Rudolph & Gruber, 2017. Anderluh et al., 2017; Choubassi et al., 2016. Naumov & Starczewski, 2019; Tipagornwong & Figliozzi, 2014. Llorca et al., 2021
Economic and Socio-economic Performance	Reference
Advantages Have lower operating costs compared to conventional delivery vehicles due to reduced fuel expenses and maintenance needs. Businesses can attract environmentally conscious customers and enhance their green branding by adopting ECCs for delivery. Introduction and scaling of ECC operations can potentially lead to new job opportunities in maintenance, operations, and delivery sectors. Reduced congestion, accidents, and pollution related to ECC usage can translate to societal savings.	Carracedo & Mostofi, 2022; Rudolph & Gruber, 2017; MacArthur et al., 2014. Bjørnara et al., 2019; Naumov & Starczewski, 2018 Robichet et al., 2022; Llorca et al., 2021. Dalla Chiara et al., 2023; Heinrich et al., 2016.
Disadvantages Transitioning to or integrating ECCs into an existing delivery fleet might require a substantial initial investment. In some regions or for specific businesses, ECCs might not be as economically viable due to various operational or infrastructural challenges. ECCs may increase labour costs due to longer operation times with same wage additional fixed costs to build micro depots. The economic feasibility of ECCs might depend on governmental incentives or subsidies in certain regions.	Saha et al., 2023; Choubassi et al., 2016 Carracedo & Mostofi, 2022; Cortés-Murcia et al., 2019. Llorca et al., 2021; Sheth et al., 2019. Bayliss et al., 2023; Giglio et al., 2021.

Infrastructure and Urban Context Pros and Cons of Electric Cargo Bikes	Reference
Advantages Can maneuver through narrow lanes, pedestrian zones, and restricted areas, allowing deliveries in dense urban contexts. They require less parking and road space compared to larger delivery vehicles, which can be crucial in congested cities. Can be used on existing bike paths, reducing the need for specialized or additional road infrastructure. Their rise in popularity can prompt cities to invest in and expand bike-friendly infrastructure.	Robichet et al., 2022; Shojaei, 2020. Moolenburgh et al., 2020; Gruber & Kihm, 2016. Hess & Schubert, 2019; Tipagornwong & Figliozzi, 2014 Llorca et al., 2021; Enthoven et al., 2020.
Disadvantages Certain urban designs or terrains, especially those with steep inclines, might limit the range and efficiency of ECCs. As they integrate into traffic, ECCs can face potential conflicts with other road users, especially in areas without dedicated bike lanes. The safety and efficiency of ECC operations often depend on the presence of well-maintained bike lanes and secure parking or storage areas.	Caggiani et al., 2021; Naumov & Starczewski, 2019 Rudolph & Gruber, 2017; Gruber et al., 2014. Bjørnarå et al., 2019; Moolenburgh et al., 2019; Nürnberg, 2019; Sheth et al., 2019; Niels & Bogenberger, 2018; Faxér et al., 2018; Rudolph & Gruber, 2017; Greibe & Buch, 2016; Wrighton & Reiter, 2016; Schliwa et al., 2015; Tipagornwong & Figliozzi, 2014.

Technical and Performance	Reference
Advantages Electric assistance boosts rider's efforts, enabling longer distances, and managing larger loads with less fatigue. Many ECCs can be modified with different storage solutions or add-ons to suit various types of cargo. They generally have fewer moving parts than traditional vehicles, leading to reduced maintenance needs and costs. Have a much higher energy efficiency compared to gasoline-powered vehicles, translating into lower energy costs per mile.	Robichet et al., 2022; Giglio et al., 2021 Rajendran & Harper, 2021; Moolenburgh et al., 2020. Cortés-Murcia et al., 2019; MacArthur et al., 2014. Narayanan & Antoniou, 2022; Heinrich et al., 2016.
Disadvantages Battery capacity determines the range of ECCs, and recharging can take time, limiting continuous operations. Despite their adaptability, ECCs have a maximum payload capacity, which can be limiting for larger deliveries. Continuous heavy loads can strain the cycle's structure over time, leading to wear and potential breakdowns. The performance and efficiency of ECCs are dependent on advancements in battery technology and electric drivetrain innovations.	Enthoven et al., 2020; Gruber & Kihm, 2016. Dalla Chiara et al., 2023; Caggiani et al., 2021. Bayliss et al., 2023; Hess & Schubert, 2019. Schünemann et al., 2022; Serrano-Hernandez et al., 2021.

Safety and Health	Reference
Advantages Riders are exposed to less pollution compared to car drivers, leading to better respiratory health outcomes. While the electric assist provides help, riders still engage in moderate physical activity, promoting cardiovascular health. Compared to larger vehicles, ECCs present a lower risk of causing severe accidents to pedestrians or other road users.	Carracedo & Mostofi, 2022; Bjørnarå et al., 2019. Shojaei, 2020; Bjørnarå et al., 2019. Lachapelle et al., 2021; Naumov & Starczewski, 2019; Tipagornwong, & Figliozi, 2014.
Disadvantages In areas without dedicated bike lanes or with unclear road-sharing rules, ECCs could be involved in traffic conflicts with larger vehicles. Over-dependence on the electric assist can lead to decreased physical activity levels, potentially undermining some health benefits of cycling. Riders are more exposed and could be more vulnerable to injuries in the event of a collision with a larger vehicle. Carrying heavy loads without the proper posture or cycle adjustments can lead to ergonomic issues or injuries over time.	Niels et al., 2018; Anderluh et al., 2017 Saha et al., 2023; Llorca et al., 2021 Choubassi et al., 2016; Rudolph & Gruber, 2017 Hess & Schubert, 2019; Giglio et al., 2021

Environmental	Reference
Advantages Produce zero direct emissions, which can significantly reduce greenhouse gas emissions when replacing motor vehicles for delivery and transport purposes. Unlike combustion engines, electric cycles don't release harmful pollutants, leading to better urban air quality. Operate more quietly than traditional delivery vehicles, helping reduce noise pollution in urban areas. Consume less energy compared to larger electric or gasoline-powered vehicles.	Llorca et al., 2021; Gruber et al., 2014; MacArthur et al., 2014. Rajendran & Harper, 2021; Heinrich et al., 2016. Narayanan & Antoniou, 2022; Serrano-Hernandez et al., 2021. Moolenburgh et al., 2020; Cortés-Murcia et al., 2019.
Disadvantages The batteries used in ECCs might pose environmental concerns upon disposal, especially if not recycled or disposed of properly. The extraction of resources (like lithium) for battery production can have environmental impacts, including habitat destruction and pollution. While ECCs themselves emit no greenhouse gases, there are emissions associated with electricity production, especially in regions that rely heavily on fossil fuels. The implementation of alternative fuels and vehicles for inner-city deliveries is considered a moderately effective urban freight strategy with medium applicability in some countries' context.	Dalla Chiara et al., 2023; Schünemann et al., 2022; Caggiani et al., 2021. Bayliss et al., 2023; Rudolph et al., 2022; European Environment Agency, 2018. Robichet et al., 2022; Ormond et al., 2019; Naumov & Starczewski, 2018; Athanassopoulos et al., 2016. Llorca & Moeckel, 2021; Giuliano et al., 2013.

2.3.2. Barriers to Adoption

One of the primary obstacles in the adoption of ECCs is their capital cost. Their high purchase price, compared to conventional bicycles, poses a significant financial barrier. The market price

for ECCs ranges between 2,000€ (CAD 2,900) and 5,000€ (CAD 7,300), with the price range fluctuating depending on the brand and specific type of bike (Carracedo & Mostofi, 2022). This aspect was also emphasized by Palau (2021) and Rudolph & Gruber (2017) highlighting the cost challenge faced by potential adopters. In the Canadian context, for example, most of the manufacturers are based in other countries, leading to higher costs from import duties and the limited availability of ECCs.

Another factor hindering the wider acceptance of ECCs is the perceived limited electric range, which can influence the decision-making process of those considering ECCs as a viable option. Potential users are often deterred by concerns over the bikes' ability to cover sufficient distances on a single charge (Bourne et al., 2020; Jones et al., 2016; Riggs & Schwartz, 2015).

Infrastructure also plays a crucial role in the adoption of ECCs. Issues related to cycling infrastructure include the availability, condition and width of cycling lanes, maintenance, and parking facilities (Thomas, 2021; Bourne et al., 2020; Gruber & Thomas, 2020; Liu et al., 2020; Becker & Rudolf, 2018; Rudolph & Gruber, 2017; Jones et al., 2016; Riggs & Schwartz, 2015).

Moreover, there are regulatory and logistical challenges that can impede the widespread use of ECCs. Mandatory helmet usage, as well as logistical challenges related to trip distances, are among the factors that can discourage the adoption of cycle logistics (Giglio et al., 2021).

Lastly, the inclusion of ECCs in city sustainability and mobility plans is still in its early stage. While some European cities have begun implementing measures to support the use of ECCs (Carracedo & Mostofi, 2022), ECCs remain largely absent from many urban planning initiatives. This lack of integration into citywide sustainability and mobility strategies further hinders the potential growth and acceptance of ECCs in urban logistics.

In colder regions such as Canada, weather is often considered a hindrance to integrating bicycles into various activities. Dybdalen & Ryeng (2022) indicates that despite challenges posed by snow, ice, slush, and low temperatures, using cargo bikes for urban deliveries in winter is quite viable. A significant 71% of survey participants expressed comfort with cycling in temperatures down to -20°C. The primary obstacles are snow and ice on the roads. Typically, snow is viewed as more problematic than ice, largely because it increases rolling resistance, leading to greater physical exertion for cargo cyclists. This not only makes pedaling more tiring but also depletes the cargo bike's battery more quickly. Additionally, colder temperatures naturally decrease battery performance. Conversely, ice primarily presents mental challenges, requiring cyclists to be more vigilant due to longer braking distances, particularly in hilly areas or when navigating near

pedestrians. Both snow and ice complicate ascending hills, and descending becomes riskier with extended braking distances.

In a similar vein, rain appears to have a low impact on the cargo biking system. Despite heavy rain, cargo bikes maintain a steady speed. Riders, equipped with goggles, proper attire and a drying cabinet, find working in rain manageable according to Dybdalen & Ryeng (2022).

Although the challenges are clearly outlined, ECCs have been with us since the 19th Century (Momentum MAG, 2012). From their introduction to the present day, a variety of solutions have been explored and identified to facilitate their integration into urban settings. This integration extends beyond logistics to encompass everyday use by individuals.

2.3.3. Potential Solutions to Adoption

Regulatory measures can significantly enhance the adoption of ECCs in urban environments. For example, increasing parking fines for traditional vehicles and parking restrictions strategies encourage a positive shift (Choubassi et al., 2016; Schliwa et al., 2015; Tipagornwong & Figliozi, 2014; Lenz and Riehle, 2013). Additionally, the establishment of zero-emission zones, traffic restrictions (Rudolph & Gruber, 2017; Wrighton & Reiter, 2016; Schliwa et al., 2015) and no-truck zones within Central Business Districts (CBDs) (Choubassi et al., 2016).

Local public authorities play a significant role in boosting ECC use by providing affordable access to urban distribution centres and endorsing pilot projects (Navarro et al., 2016; Athanassopoulos et al., 2016). Cities can integrate cargo cycles into municipal fleets for various services, supporting their broader use, as suggested by Narayanan & Antoniou (2022) and Wrighton and Reiter (2016). ECCs can also gain wider acceptance in the planning process if they are incorporated into city master plans. A comprehensive sustainable urban transport initiative, involving regional collaborations and partnerships, is crucial for their success (Koning & Conway, 2016; Rudolph & Gruber, 2017).

A robust cycling infrastructure is also necessary for ECCs in commercial transport. Enhancements are needed in expanding and connecting bike lane networks, building exclusive cycling paths, and optimizing intersections for cycle traffic. Additionally, making parking, maintenance and storage facilities more accessible would facilitate ECC adoption. (Saha et al., 2023; Dalla Chiara et al., 2023).

Despite their advantages, the current presence of ECCs in commercial settings remains marginal, specially in Canada. The number of companies replacing conventional vehicles with ECCs is limited, and private logistics like shopping errands represent a significant potential market for

cargo cycles. Awareness of their cost-effectiveness and applications is not yet widespread, and adoption often relies on the personal interest and experiences of decision-makers (Rudolph & Gruber, 2017).

Finally, ECCs are under-researched, leading to gaps in understanding their operation, interaction with urban infrastructure, and impacts on other road users. To address this, cities are conducting pilot studies to collect more data on cargo cycles (Purolator Inc., 2022; City of Toronto, 2021; Hu & Haag, 2019; Baruchman, 2018). The research in this thesis will help contribute towards these efforts by focusing on the collection and analysis of ECC battery performance.

2.4. Data Collection

Pilot studies in transportation rely on the consistent gathering of relevant data. Data collection for ECCs sheds light on various aspects of their performance, such as how often ECCs are used, their battery efficiency, and the challenges faced during operations. Such information is crucial to enhance the way ECCs are integrated into urban freight delivery networks. However, Reggiani et al. (2022) emphasize that the mere presence of data collection technologies does not guarantee that data will be effectively gathered and utilized. Therefore, the structure of the data and the underlying technology play a critical role in this process.

Dalla Chiara et al. (2023) used a multichannel approach, utilizing a blend of video, Global Positioning System (GPS), delivery, and infrastructure data. Video cameras on ECCs provided the driver's perspective, while GPS data were captured at 20-second intervals using mobile devices. Delivery data, encompassing location and time details of each delivery, were integrated with GPS traces and road segment characteristics from GIS layers, enabling a comprehensive analysis of ECC operations.

Other researchers joined the growing list using GPS in their research for various vehicle types (Zakhem & Smith-Colin, 2021; Oskarbski et al., 2021; Vasiutina et al., 2021; Melo & Baptista, 2017). Laranjeiro et al. (2019) highlighted the rapid increase in the use of GPS devices, facilitating the analysis of spatial and temporal trends in city logistics. Gruber & Narayanan (2019) compared the trip times of ECCs with those of motorized vehicles using Google Maps data, finding that about half of the commercial transport trips switched from cars to cargo cycles wouldn't be delayed more than 2-10 minutes. Across various European cities, Moolenburgh (2019) implemented GPS and cameras for vehicle monitoring, while Lopez et al. (2017) documented approximately 10,000 e-bike trips using GPS. Marujo et al. (2018) applied similar technology to ECCs in Rio de Janeiro, and Dalla Chiara & Goodchild (2020) did the same for commercial

vehicles in Seattle, USA. Straka & Buzna (2018) leveraged GPS data to assess energy consumption, making assumptions about charging patterns. Despite the long list, there is a geographical bias in the use of GPS data from freight vehicles with a predominance of data coming from developed countries and a scarcity from developing and emerging economies. This gap hinders the capacity of these countries to enhance transport operators' logistical planning and the strategic policymaking of public entities (Laranjeiro et al., 2019).

Devices with built-in GPS, complemented by various sensors, are increasingly used for detailed data collection, particularly in the context of ECC operations. Oztay et al. (2014) and Toglaw et al. (2018) highlighted the necessity of sensors for measuring parameters such as speed, energy consumption, atmospheric pressure, and ambient temperature (Dybdalen & Ryeng, 2022; Mello Bandeira et al., 2019; Bjørnara et al., 2019).

Temporelli et al. (2022) introduced the MOSCA (MOnitoring System for CArgobike) to track energy consumption parameters during recharging and actual delivery services in Padua, Italy. Puma-Benavides et al. (2021) implemented an intelligent energy management system in ECCs, utilizing sensors to optimize the use of onboard stored energy. This system takes into account factors like air temperature and the currents and voltages of motors and batteries, demonstrating the diverse and sophisticated applications of sensor technology in ECC operations and research.

Rudolph et al. (2022) leveraged Geographical Information Systems (GIS), incorporating data from OpenStreetMap and Google Maps to obtain intricate urban layout details crucial for planning and analyzing ECC routes. GIS is increasingly being used for data preparation, visualization, and analysis. Alattar et al. (2021) employed QGIS for such purposes. Papaioannou et al. (2023) managed to get road gradients and travel costs using QGISTM and Google Maps, respectively. Several other researchers have harnessed the capabilities of Google Maps APIs (Fontaine, 2022; Hesselmanns, 2022; Allen et al., 2021; Fiori & Marzano, 2018; Naumov & Starczewski, 2018) and OpenStreetMap (Alattar et al., 2021; Arnold et al., 2017) for diverse data collection purposes.

Similar to the GPS devices, mobile devices, equipped with an array of sensors, have become pivotal in enhancing the data collection process. Gruber & Narayanan (2019), Fiori & Marzano (2018), and Ferreira et al. (2017) all used mobile devices for their research, leveraging sensors like accelerometers and gyroscopes. These sensors are essential for accurately tracking and analyzing ECC movements.

Smartphones, in particular, have revolutionized the way cycling data is captured, enabling the collection of vast amounts of information. Strava Labs (2023) is a notable example, encompassing

trillions of GPS data points from its extensive dataset. Strava, an app combining physical exercise tracking with social networking features, represents a significant source of this cycling data. Beyond Strava, Bike Data Project (2023) offers a platform that aggregates cycling data from various applications, including Strava, under the principles of open source and open data.

Recognizing the convenience and effectiveness of apps in collecting cycling data, several cities have developed their own applications. The European Cyclist Federation (2023) highlights several city-specific apps such as See.Sense (used in the UK, Ireland, and other locations), Bike your City (Athens/Greece), Ring Ride (Vienna/Austria), Cykelstaden (Gothenburg), Bike citizen, GéoVélo (for French cities), Strava Metro, Bikes vs. Cars (in Malmö/Skåne and by Cykelfrämjandet), and BikePrint (Netherlands).

Additionally, social media platforms provide another avenue for data collection. Pavlyuk et al. (2018) demonstrated the utility of the Twitter API for gathering urban transport data, suggesting the potential of social media platforms as rich sources of information in this field.

In addition to GPS technology, other sophisticated tools and methods are being employed to deepen the understanding of ECC usage patterns. For instance, Camomilla et al. (2015) used gyroscopes to collect data on vibrations across different axes, angular speed, components of the magnetic field vector, and both gravitational and inertial accelerations. These types of sensors provide a more nuanced understanding of the physical dynamics involved in ECC operations.

Online surveys have also become a valuable tool for gathering sociodemographic data, as demonstrated by Serrano-Hernandez et al. (2021). This method allows researchers to collect a wide range of information directly from users, offering insights into the demographics and preferences of ECC riders.

Furthermore, Kiefer & Behrendt (2016) designed the smart e-bike monitoring system, which integrates custom sensors (like those mentioned above) with real-time GPS location tracking. This system also includes control features for the level of assistance in Pedelec. Such systems not only provide valuable data on the bike's performance and usage patterns but also enhance the riding experience by adjusting to the rider's needs. These diverse technological approaches collectively contribute to a more thorough understanding of ECC usage, performance, and potential areas for improvement in urban logistics.

Table 5 summarizes the diverse range of devices and technologies employed in the data collection process for ECCs. The widespread use of GPS in various studies underscores its crucial role in collecting vast amounts of real-time data and its significance as a rich source of

information for modeling freight systems (Sharman and Roorda, 2011). However, despite recent advancements in measurement methods and sensor technology, acquiring and processing cycling mobility data remains a challenge (Oskarbski et al., 2021).

Table 5: Technology for ECC Data Collection

Technology	Data	Reference
GPS	Tracking location, speed, and routes.	Dalla Chiara et al., 2023; Dalla Chiara & Goodchild, 2020; Zakhem & Colin, 2021; Oskarbski et al., 2021; Vasiutina et al., 2021; Laranjeiro et al., 2019; Gruber and Narayanab, 2019; Moolenburgh, 2019; Marujo et al., 2018; Straka & Buzna, 2018; Lopez et al., 2017; Melo & Baptista, 2017; Gingerich et al., 2016.
GIS (e.g., QGIS, Google Maps, Open Street Maps)	Detailed urban layout data, route planning, data preparation, visualization, and analysis.	Papaioannou et al., 2023; Rudolph et al., 2022; Fontaine, 2022; Hesselmanns, 2022; Allen et al., 2021; Alattar et al., 2021; Gruber and Narayanab, 2019; Fiori & Marzano, 2018; Naumov & Starczewski, 2018; Arnold et al., 2017.
Apps/Smartphones (e.g., Strava, Twitter, See.Sense, Ring Ride)	Large-scale cycling data collection, social media insights.	European Cyclist Federation, 2023; Gruber & Narayanan, 2019; Fiori & Marzano, 2018; Pavlyuk et al., 2018; Ferreira et al., 2017; Strava Labs; Bike Data Project.
Video Cameras	Visual data collection for monitoring and analysis.	Dalla Chiara et al., 2023; Moolenburgh, 2019.
Sensors (Gyroscope, heart rate)	Vibrations, heart rate, angular speed, components of the magnetic field vector, and both gravitational and inertial accelerations.	Camomilla et al., 2015; Walter et al., 2011.
Commercial Devices (e.g., Garmin, CatEye Velo 9)	Comprehensive cycling data including data from GPS, GIS and sensors. Mostly integrated with apps.	Dybdalen & Ryeng, 2022; Mello Bandeira et al., 2019; Bjørnará et al., 2019; Kiefer & Behrendt, 2016.
Energy Meter (e.g., MOSCA)	Energy consumption parameters (Current, Voltage, state of charge).	Temporelli et al., 2022; Benavides et al., 2021; Toglaw et al., 2018; Oztay et al., 2014.
Surveys	Sociodemographic information and mobility habits of users / companies	Dybdalen & Ryeng, 2022; Serrano-Hernandez et al., 2021; HUB Cycling, 2020; Becker & Rudolf, 2018; Riggs, 2016

2.5. Modelling

2.5.1. Battery Performance

Batteries are pivotal component for ECCs for energy storage, power management, efficiency, cost, and environmental impact of transportation and logistics operations. The literature presents a variety of models that analyze and optimize battery usage in different transportation scenarios. These models range from simple estimations of energy consumption rate by multiplying the trip distance with the battery discharge rate (Ji et al., 2014), to more sophisticated models that estimate the power usage and maximum achievable distance of an electric or traditional truck, based on speed and load weight (Davis & Figliozzi, 2013). Each model offers unique insights into the complexities of battery usage, highlighting factors such as vehicle mass, battery discharge rates, and the influence of environmental conditions.

One of the challenges in battery-based transportation systems is optimizing battery capacity and energy consumption relative to factors like vehicle mass, route slope, and cargo loads. Rudolph & Gruber (2017) determined that steeper slopes can be a challenge for ECCs. Papaioannou et al. (2023) evaluated the consumption rate for commercial ECCs by using an average energy consumption of 10 Wh/km, proposed by Nocerino et al. (2016) and an adjustment factor based on road slope. This factor, recommended by Arango et al. (2021), considers the slope of each route segment, revealing that energy consumption escalates with speed due to increased drag force on identical slopes. With this approach, Papaioannou et al. (2023) found that total energy consumption tends to decrease nearly linearly with higher load capacities, while the distance increases alongside capacity. However, both studies, Papaioannou et al. (2023) and Arango et al. (2021), provide limited exploration into the specific effects of road slope. They also highlighted how these considerations are often neglected in relevant vehicle routing problems (VRPs).

Weiss et al. (2020) noted a close relationship between battery capacity and vehicle mass, based on technical data found in different models of electric passenger cars. Increasing the battery capacity of electric cars by 10 kWh results in a weight gain of 15 kg, extends the driving range by 40–50 km, and raises the energy consumption by 0.7–1.0 kWh per 100 km.

Hesselmans (2022) noted that the cost of travel increases with heavier vehicle loads, primarily because driver wages constitute a larger expense than fuel costs when optimizing for cost efficiency. The considerations made in these models, don't rely on experimental data, but empirical estimations based on other studies and technical sheet information.

Duin et al. (2013) noted that environmental temperature and route slope strongly influence battery performance. However, quantifying these effects on operation limits was beyond their research scope. Fiori & Marzano (2018) developed a microscopic energy consumption model for Electric Freight Vehicles (EFVs). They evaluate the energy consumption as a function of second-by-second vehicle speed, actual real weight onboard, roadway grade and vehicle characteristics. The model considers regenerative braking systems and it's not designed for ECCs.

Fontaine (2022) introduced the vehicle routing problem with load-dependent travel times for ECCs. This model considers extra weight, slope and time windows to calculate travel times. It reveals that travel times could be reduced by up to 22% when time windows are larger compared to traditional approaches. Fontaine (2022) primarily considers the cyclist as the key energy source, using constant power profiles to gauge the cyclist's contribution to the system. However, they acknowledged the need to explore variable power profiles, as power output can differ significantly among cyclists for various reasons.

A typical person can sustain 100 W of power while cycling, leading to a combined available power of 350 W when including battery power. This interplay between cyclist and battery power not only augments the total power but also helps in reducing battery consumption (Fontaine, 2022). Based on this model, Hesselmans (2022) enhanced its computational efficiency, integrating additional factors such as wind speed and direction.

Despite the contributions of existing research, including these last models, there's a noticeable lack of in-depth analysis on how different factors influence battery performance in ECCs. This shortfall is particularly prominent in micro-level route optimization for ECCs, where the interplay between such factors and their collective impact on outcomes remains underexplored, focusing mainly on route attributes without adequately considering battery dynamics as influenced by a range of external conditions. Critical battery-related factors like voltage, state of charge, discharged energy, and current are often overlooked. Most studies tend to concentrate on route optimization outcomes such as time, distance, and cost, without separately examining battery behavior, which is significantly affected by variables including road slope, the weight of the load and driver, temperature, and the level of assistance provided, the latter being a crucial but frequently neglected element in ECC research.

2.5.2. Route Optimization Modelling

The research in urban delivery systems involving ECCs, tends to focus on the development of logistic systems rather than enhancing the technical aspects of the vehicles themselves

(Temporelli et al., 2022). This underscores a significant gap in existing studies. Despite the topic of route optimization being explored since 1959, its application to ECCs remains notably underexplored.

Table 6 emphasizes the crucial role of choosing loading point or depot locations in the development of cargo distribution systems, showcasing studies that delve into the macroscopic simulation where the positioning of depots is key, both for entities operating their fleets on a daily basis and for city planning purposes. The majority of these models prioritize depot location identification, essential for city planners to gain a comprehensive understanding of the logistics landscape within their areas of management. While some studies are dedicated to optimizing routes, which indirectly informs depot placement, these particular models do not aim to solve the location challenges directly but rather to explore the dynamics among established facilities and the interplay of different transportation modes. Out of the 32 models reviewed, 13 incorporate ECCs among the modes of transport analyzed, yet none focus exclusively on ECCs, which differ notably from electric vehicles, traditional bikes, vans, and other categories considered in these studies, as well as the influencing factors.

Table 6: Optimization Models for Depot Location, Battery Charging, and Vehicle Routing

Research	Objective	Vehicle	Reference
Designing a multi-modal and variable-echelon delivery system for last-mile logistics	Depot location	Vans, ECCs, Porters	Bayliss et al., 2023
Two-echelon city distribution scheme with temporal and spatial synchronization between cargo bikes and vans	Depot location	Vans, ECCs	Anderluh et al., 2021
Designing multi-tier, multi-service-level, and multi-modal last-mile distribution networks for omni-channel operations	Depot location	Multi-modal	Janjevic et al., 2021
Synchronization measurement model for the distribution centre operation synchronization (DCOS) problem	Depot location	Trucks	Yu et al., 2020
Impact Assessment Model for the Implementation of Cargo Bike Transshipment Points in Urban Districts	Depot location	ECCs	Assmann et al., 2020
The two-echelon vehicle routing problem with covering options: City logistics with cargo bikes and parcel lockers	Depot location	Trucks, ECCs	Enthoven et al., 2020
Quantifying environmental and financial benefits of using porters and cycle couriers for last-mile parcel delivery	Depot location	Porters, ECCs	Martinez-Sykora et al., 2020
Simulation–optimisation framework for building instances and assess operational settings.	Depot location	Vans, bikes, ECCs	Perboli & Rosano, 2018

Research	Objective	Vehicle	Reference
Simultaneous facility location and vehicle routing problem that arises in health care logistics	Depot location	Not specified	Veenstra et al., 2018
Two echelon open location routing problem	Depot location	Not specified	Pichka et al., 2018
Two-echelon capacitated vehicle routing problem with environmental considerations in city logistics service	Depot location	Fossil fuel vehicles	Wang et al., 2017
Location routing model that integrates the choice between self-operating and subcontracting a depot	Depot location	Not specified	Stenger et al., 2012
Assessment of the potential of cargo bikes and electrification for last-mile parcel delivery by means of simulation of urban freight flows	Depot location	E-Vans, ECCs	Llorca et al., 2021
Delivering on the last mile by cargo bicycles and rerouting of parcels to pick-up points	Depot location	ECCs	Zhang et al., 2018
Location-routing Problem with Intra-route Facilities	Depot location, recharging, swapping	EVs	Schiffer et al., 2018
Battery swap station location-routing problem with capacitated electric vehicles	Depot location, swapping	EVs	Yang & Sun, 2015
Two-echelon location-routing problem for biomass logistics systems	Route optimization	Not specified	Cao et al., 2021
Two-phase local search with a discrete-event heuristic for the omnichannel vehicle routing problem	Route optimization	Cargo vehicles	Bayliss et al., 2020
Collaborative urban cargo distribution system for logistics service providers, based on a transshipment terminal and usage of electric cargo bikes	Route optimization	ECCs	Ormond Junior et al., 2019
Two-echelon city distribution scheme with temporal and spatial synchronization between cargo bikes and vans	Route optimization	ECCs, Vans	Anderluh et al., 2017
Two-echelon vehicle routing problem with time window and synchronization constraints, and multiple trips at the second level.	Route optimization	Not specified	Grangier et al., 2016
Multi-Depot Two-Echelon Vehicle Routing Problem with Delivery Options	Route optimization	Not specified	Zhou et al., 2018
Heterogeneous fleet green vehicle routing problem (HF-G-VRP)	Route optimization	Vans, E-Vans, Bikes, ECCs,	Shojaei, 2020
Capacitated vehicle routing problem with time window	Route optimization	Long Life Vehicles (LLV), Vans, ECCs	Choubassi et al., 2016

Research	Objective	Vehicle	Reference
Two-Echelon Vehicle Routing Problem (2E-VRP) and the Location Routing Problem (LRP)	Route optimization, depot location	Not specified	Hemmelmayr et al., 2012
Two-echelon electric vehicle routing problem with time windows and partial recharging	Route optimization, recharging	E-Vans, ECCs	Caggiani et al., 2021
The electric vehicle routing problem with time windows, partial recharges and satellite customers	Route optimization, recharging	EVs, bikes, drones, segways	Cortés-Murcia et al., 2019
The electric location routing problem with time windows and partial recharging	Route optimization, recharging	EVs	Schiffer & Walther, 2017
Vehicle Routing and Location Routing with Intermediate Stops	Route optimization, recharging	EVs	Schiffer et al., 2019
The electric vehicle routing problem with partial charge, nonlinear charging function, and capacitated charging stations	Route optimization, recharging	EVs	Froger et al., 2017
The electric vehicle routing problem with nonlinear charging function	Route optimization, recharging	EVs	Montoya et al., 2017
The dial-a-ride problem with electric vehicles and battery swapping stations	Route optimization, swapping	EVs	Masmoudi et al., 2018

There is a general, but informal consensus, on the fact that the challenges involving vehicles within the logistic realm require the development of a route optimization process. This is where the Vehicle Routing Problem (VRP) becomes essential, explaining why some researchers integrate depot location with route optimization in their studies.

The VRP, first introduced by Dantzig & Ramser (1959), is an integer programming problem that aims to optimize the allocation of routes for a fleet of vehicles with delivering goods for multiple destinations. The main objective of VRP is to reduce total operational expenses, encompassing factors such as travel distance, fuel usage, and time incurred, while simultaneously fulfilling all delivery obligations.

The VRP has evolved to include various aspects such as carrying capacity (Golden et al., 1983), time windows, pickup and delivery services (Ropke & Pisinger, 2006). Further adaptations have combined carrying capacity with time windows (Pisinger & Ropke, 2007), profits (Ahn et al., 2012), and emissions (Bektaş & Laporte, 2011; Jabali et al., 2012).

The study of VRP in the context of electric vehicles (EVs) was first undertaken by Artmeier et al. (2010) who introduced modifications to existing shortest-path algorithms to cater to energy-

efficient routing for EVs. However, it was the study by Schneider et al. (2014), which presented the electric vehicle routing problem with time windows and recharging stations, that significantly heightened interest in the field. This surge in attention was particularly influenced by the launch of the Tesla Model S in 2012, a vehicle that revolutionized the automotive industry as the first mass-produced and widely accessible electric sedan (Tesla, 2012).

The research by Schneider et al. (2014) was extended by Goeke & Schneider (2015) to include mixed fleets of electric commercial vehicles (ECVs) and internal combustion commercial vehicles (ICCVs). Further contributions by Schneider et al. (2015) incorporated intermediate stops, which include stops for good replenishment, refueling, and waste disposal. Keskin & Çatay (2016) introduced strategies for partial battery recharging. Huang et al. (2017) refined the VRP model by incorporating path flexibility, allowing for multiple optional routes between customer pairs. This approach recognizes the dynamic nature of road conditions and traffic, leading to more adaptable and efficient route planning. The research by Zachariadis et al. (2015) and Corberán et al. (2018) added a new dimension by focusing on load-dependent costs, thereby incorporating the varying expenses associated to vehicle weight, fuel consumption and speed into the vehicle routing challenge.

Up to now, the majority of models developed for electric vehicles have been tailored for electric cars, with only a few being suitable for ECCs due to their unique operational characteristics, which differ significantly from cars. Llorca et al. (2021) and Caggiani et al. (2021) concentrated their studies on the constraints and energy usage of ECCs. Their research shed light on key elements that influence the efficiency and feasibility of ECCs in urban delivery systems. Those key elements encompass the potential of ECCs to decrease the reliance on motorized vehicles, though larger parcels may still necessitate their use. Additionally, the rise in total operation time upon transitioning to ECCs, alongside considerations of initial investment in vehicles, drivers' wages, and the expenses associated with micro-depots.

Similarly, Fontaine (2022) introduced a novel approach to the vehicle routing problem for ECCs by integrating load-dependent travel times into the model. This innovative method considers the impact of cargo weight and road gradient on ECC performance. Factors including heavier loads, steeper slopes, and lower power increase the total energy consumption of the vehicle battery. The model results in a decrease in travel time, while comparing different time windows, cargo weight and slope. Minimizing travel time is their objective function. The emphasis on travel time as the objective function arises from low battery replacement and energy costs when compared with labor expenses.

Despite these advancements, it's evident that there are still a limited number of models that take into account the distinct attributes of ECCs in practical scenarios. Moreover, among those that do consider certain factors, many fail to explore their interconnections beyond the confines of route optimization. This lack of comprehensive models underscores the necessity for more in-depth research aimed at optimizing the use of these vehicles. Conducting such studies is vital for improving the efficiency and effectiveness of urban delivery networks, especially as they begin to rely more heavily on e-bikes and ECCs.

Table 7 offers a detailed overview of the objective functions, constraints, and variables included in similar models for ECCs. Papaioannou et al. (2023) focused on minimizing energy consumption by adjusting the average energy consumption per distance unit, influenced by a multiplicative factor related to the slope of the road. However, in their model, the slope is implied, and while avoiding hills is considered, there is no clear definition of what constitutes a hill.

Fontaine's (2022) model closely aligns with the one proposed in this study. However, this thesis goes further than Fontaine's methodology, which assumes uniform power output from cyclists, by incorporating variables like assistance level, battery range, and energy consumption, along with conditions like state of charge (SoC), diversity in the vehicles employed, and battery swapping strategies. The objective of this research is to ease the physical strain on the rider by reducing distance and lower the energy use per trip, thereby prolonging the battery's lifespan.

Table 7: Route Optimization Models for ECCs

	Papaioannou et al., 2023	Fontaine, 2022	Garcia, 2024
Model	E-cargo bike routing model for urban deliveries	Vehicle routing problem with load-dependent travel times with ECCs (VRPLTT)	Electric Cargo Cycle Routing Problem
Objective Function	Minimize energy consumption	Minimize total travel time	Minimize distance
Constraints			
Single customer visit	X	X	X
Sub-tour elimination	X		X
Single depot	X	X	X
Homogeneous Fleet	X	X	X
Load capacity	X	X	X
Time Windows		X	
Heterogeneous Fleet			X
State of Charge			X
Battery swapping			X
Variables			
Distance	X	X	X
Weight	X	X	X
Speed		X	X
Wind Speed		X	
Slope	X	X	X
Energy Consumption	X		X
Cargo box		X	
Assistance level			X
Battery Range			X
Temperature			X

2.6. Chapter Summary

This chapter explores the dynamic world of micromobility, with a special focus on Electric Cargo Cycles (ECCs) and how they fit into urban logistics frameworks. It starts with an overview of the micromobility concept, showcasing its potential to provide efficient travel options for short to medium distances within urban centres. The chapter covers micromobility's definitions, vehicle types, and its rapidly growing market, alongside a comprehensive examination of ECCs. This examination includes their historical development, technological progress, and their crucial role in promoting sustainable urban transport.

Insights into the global and Canadian micromobility markets are presented, detailing the technological advancements and adoption trends of micromobility vehicles, particularly ECCs,

emphasizing their rising market dominance and the efforts by municipalities around the globe to embed micromobility solutions into their transport strategies. It also discusses the development, categorization, and increasing involvement of ECCs to address the challenges of last-mile delivery within densely populated areas.

Moreover, the chapter addresses ECC design, focusing on various important aspects like payload capacity and its optimization challenges; power output and its regulatory implications; and battery technology. The latter's crucial role in ECC performance is analyzed, examining how factors like discharge rates, environmental conditions, and cargo loads affect operational range and efficiency. It also tackles the environmental challenges posed by battery usage in ECCs and how optimization strategies can mitigate these impacts, albeit with potential cost trade-offs.

Urban logistics and the transformative effect of e-commerce growth on delivery systems are analyzed, pinpointing ECCs as strategic enhancers of urban delivery networks. The narrative delves into the factors driving ECC adoption and the barriers hindering its widespread uptake, such as high initial costs, concerns over electric range, and regulatory hurdles.

Potential remedies to facilitate ECC adoption are proposed, highlighting the importance of regulatory frameworks, initiatives by public authorities, and infrastructure enhancements. Innovative data collection methods, including the use of GPS technology, sensors, and mobile devices, are discussed as essential tools for optimizing ECC integration into urban freight systems.

The latter parts of the chapter concentrate on modeling strategies aimed at refining ECC operations, especially regarding battery performance and route optimization. Various models are reviewed, from straightforward energy consumption calculations to complex algorithms accounting for variables like vehicle mass, route inclination, and cargo weight. The discourse on route optimization modeling underlines the little integration of ECCs into these models, stressing the urgent need for additional research to boost ECC efficiency in urban delivery contexts.

A comparative analysis between existing ECCs and the novel contribution of this thesis is presented, with the latter going beyond previous methodologies by integrating factors such as assistance level, battery range, energy consumption, state of charge (SoC), vehicle diversity, and battery swapping strategies. This comprehensive approach not only aims to alleviate physical strain on riders but also to enhance energy efficiency per trip, extending the battery's operational lifespan.

3. Methodology

This chapter introduces the methodology used to get the necessary results, aiming to shed light on the operational capabilities, limitations, and optimization potential of ECCs in an urban setting.

The methodology combines real-world data collection with analytical techniques, introducing the concepts of polynomial regression, random forest, and neural network, to model and understand the complex dynamics of battery metrics and other variables.

Furthermore, this chapter introduces the Electric Cargo Cycle Routing Problem (ECCRP) and its enhanced counterpart, the E-ECCRP, as novel frameworks for optimizing ECC usage within the constraints of battery range and load capacity.

This introductory overview sets the stage for a detailed exploration of the research findings in subsequent chapters.

3.1. Data Collection

3.1.1. Study Area

The research was conducted within the boundaries of York University's Keele Campus. The core area of data collection centered around the Bergeron Centre for Engineering Excellence, which served as the starting, ending point, and route taken for each trip as shown in Figure 4. The route covers a distance of approximately 5 kilometers.

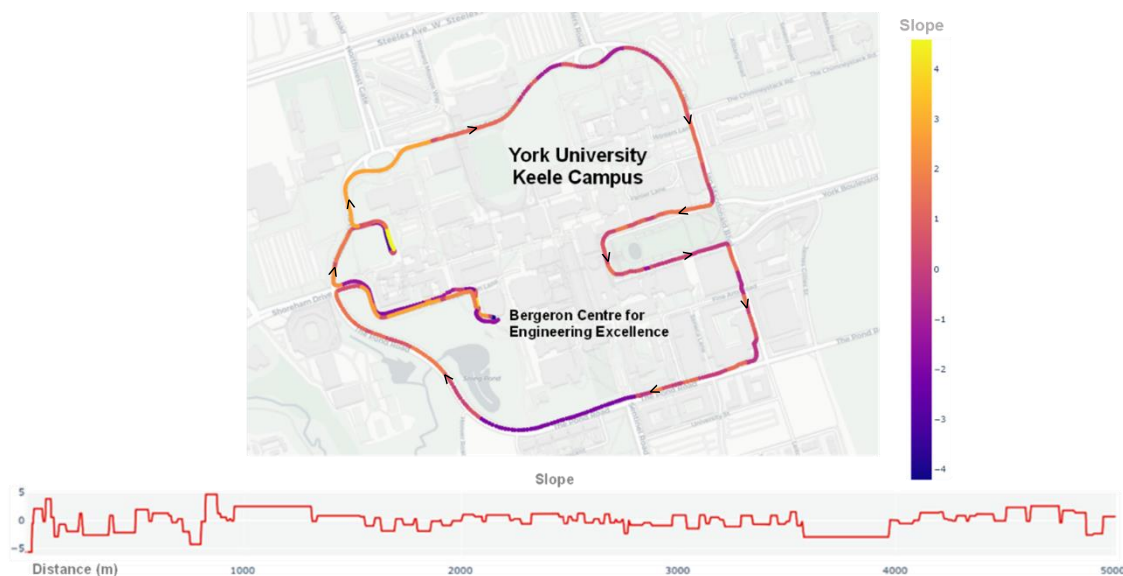


Figure 4: Study Area and Average Slope of the Route

The study area encompasses mixed streets, providing a realistic urban environment that includes a variety of interactions and physical challenges. The route is selected to include varying slopes, intersections with motor vehicles, and areas of pedestrian traffic. Each trip is conducted under 'free flow' conditions, allowing riders the autonomy to choose a comfortable speed.

Figure 4 also presents the slope variations encountered along the route based on the elevation data sourced from Google Map. It highlights the diverse topographical challenges present in the study area, including sections of substantial incline and decline.

3.1.2. Equipment

Two different models of ECCs are employed, each with unique technical specifications and originating from different companies. Table 8 presents a detailed overview of the general specifications for each of these ECCs.

Table 8: Technical Specifications of ECCs

Specification	Description	ECC 1	ECC 2
Model	Official model name	Ami Trishaw	Babboe Pro Trike XL Midmotor
Motor Power (W)	Motor's power output	500	250
Torque (Nm)	Motor's rotational force	45	70
Battery Capacity (Wh)	Energy storage capacity of the battery	624	500
Voltage (V)	Electrical potential of the battery	48	36
Max Speed (km/h)	Maximum speed the ECC can reach	25	25
Load Capacity (kg)	Maximum weight the ECC can safely carry	260	100
Battery Range (km)	Indicates how far the ECC can travel on a single charge.	30-35	50-75
Weight (kg)	Total weight of the ECC	100	90
Assistance Level	Settings that determine how much power the motor provides to assist in pedaling	5	4
Battery Type	Battery type that comes with the ECC	Lithium ion	Lithium ion
Origin	Where the bike is designed or manufactured	Canada	Netherlands

The first vehicle is ECC1, the Ami Trishaw, from now on referred as Ami, is a product of the Canadian social venture, Cycles Toussaint, specifically engineered for the transportation of the

elderly and those with mobility challenges. This model is integral to promoting the Cycling Without Age movement within Canada (Cycles Toussaint, 2024). This is a battery-assisted electric tricycle featuring a front-mounted box, designed primarily for carrying additional passengers, yet it holds the potential for transporting various types of cargo as well.

In contrast, the Babboe Pro Trike XL Midmotor, from now on referred as Babboe, originating from the Dutch brand Babboe, was introduced in 2018 with a focus on facilitating efficient 'last mile delivery' (Babboe, 2023). This ECC is distinguished by its large and sturdy box, equipped with a convenient handle and boasting a significant capacity of 900 liters. It incorporates a robust Yamaha mid-drive motor, paired with a stepless shifting system that adapts the level of pedaling assistance required. Figure 5 shows the Ami and the Babboe.

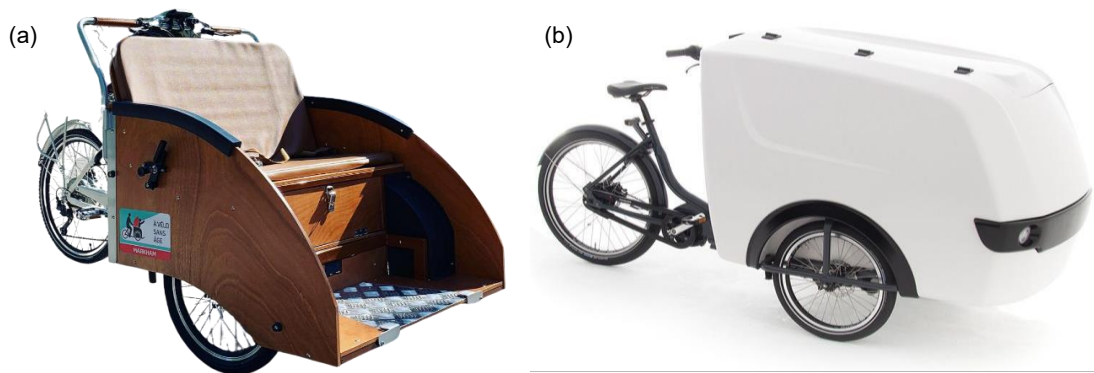


Figure 5: Research Vehicles Including (a) Ami and (b) Babboe

Devices attached to the ECC are used to gather the necessary data. The battery is monitored using the SmartShunt battery monitor by Victron Energy. This device, connecting via Bluetooth to the VictronConnect App on a smartphone, allows for the efficient monitoring of all battery parameters. A Raspberry Pi 4 equipped with the Venus OS was integrated with the device to store the data. This setup enables seamless communication with the VRM Portal, Victron Energy's advanced remote monitoring system, which provides both real-time and historical data.

A Krisdonia 25000mAh power bank was adapted to ensure compatibility with our mobile research setup. The placement of the battery monitor varied between the two ECCs. Figure 6 presents the diagram for installing the SmartShunt.

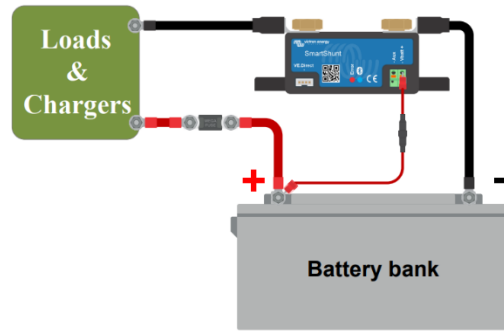


*Figure 6: SmartShunt Basic Installation
(Victron Energy, 2024)*



*Figure 7: (a) Garmin Edge 530 and (b) Speed Sensor
(Garmin, 2024)*

The vehicle trajectory is captured using the Garmin Edge 530 (a) and a speed sensor (b) as shown in Figure 7.

This comprehensive cycling computer enables the capture of detailed data points at one-second intervals, including coordinates, speed and temperature.

Diverse load weights are tested to simulate the logistic requirements of an ECC used for cargo pickup and delivery. Concrete blocks, measured on a digital scale, were positioned in the ECC's cargo box to simulate varying loads, as shown in Figure 8. Additionally, riders weighed themselves using the digital scale prior to each trip.

Figure 9 (a) and (b) visualize the SmartShunt installation in the Ami and the Babboe, respectively, Figure 9 (c) details the connections between the power bank, Raspberry Pi, and SmartShunt, and Figure 9 (d) presents an overview of the system from the rider's perspective, including the Garmin Edge 530. Ami features a similar system setup, but with the connections of (c) within the cargo box, with the Garmin Edge 530 mounted on the handlebar, akin to the Babboe configuration.



Figure 8: Load Simulation for Data Collection Scenarios



Figure 9: Device Installation on the ECCs

3.1.3. Data Collection Process

The data collection process for this study was conducted from September 27 to December 22, 2023. There were 60 trips undertaken, including 6 trips for initial calibration, adjustments and other trips that were not considered due to multiple errors with the devices attached such as not recording data or malfunction during the trip. This resulted in 46 trips, culminating in 230 km and 51,911 data points.

The process includes 15 scenarios following the same route as shown in Table 9. Each scenario is completed twice.

Two variables are prioritized when devising the various data collection scenarios for this study, including the level of battery assistance and the load weight. The load weight has practical relevance in real-world logistics operations, as evidenced by a wide range of literature (Papaioannou et al., 2023; Dalla Chiara et al., 2023; Bayliss et al., 2023; Hesselmanns, 2022; Fontaine, 2022; Temporelli et al., 2022; Caggiani et al., 2021; Aiello et al., 2021; Moolenburgh et al., 2020; Hess & Schubert, 2019; Rudolph & Gruber, 2017; Schier et al., 2016; MacArthur et al., 2014; Gruber et al., 2013). Similarly, electric assistance is identified as a key feature that enhances the cycling experience by adapting to the needs of the rider, as underscored in recent studies (Robichet et al., 2022; Giglio et al., 2021; Kiefer & Behrendt, 2016).

The level of battery assistance refers to the degree of electronic aid provided by the motor, while the weight of the package reflects the additional load being transported. These factors are expected to influence the power requirement of each ECC for completing each trip and therefore connect explicitly to ECC route models. Other potential variables, such as speed and distance, are observed but are not controlled in the scenarios. This allows the rider to adjust the vehicle according to the surrounding conditions.

Table 9 details the various scenarios considered for this process. The load weights, aimed to be approximately 50 kg and 100 kg, exhibited variations due to the concrete blocks not matching the exact target weights. As a result, the actual weights occasionally are slightly above or below these intended values ($\pm 5\%$). Additionally, certain scenarios are not feasible due to the inability of a rider to complete the entire trip without physically assisting the ECC on uphill segments by getting off and pushing the ECC or taking breaks when carrying the specified weight. Furthermore, assistance level 5 is not available for Babboe.

Table 9: Data Collection Scenarios

Data collection scenario	Weight (Kg)	Level of Assistance	ECC 1	ECC 2
W0L1	0	1	x	x
W0L2	0	2	x	x
W0L3	0	3	x	x
W0L4	0	4	x	x
W0L5	0	5	x	Level not Available
W50L1	~50	1	Not Feasible	Not Feasible
W50L2	~50	2	x	x
W50L3	~50	3	x	x
W50L4	~50	4	x	x

Data collection scenario	Weight (Kg)	Level of Assistance	ECC 1	ECC 2
W50L5	~50	5	x	Level not Available
W100L1	~100	1	Not Feasible	Not Feasible
W100L2	~100	2	Not Feasible	Not Feasible
W100L3	~100	3	x	x
W100L4	~100	4	x	x
W100L5	~100	5	x	Level not Available

The data collection process is shown in Figure 10. A pre-trip checklist completed using Google Forms captured essential details including the date, time, ECC, rider's weight, load's weight, and the level of assistance used.

This check is performed at the designated start point. Key steps include ensuring the battery monitor is synchronized to 100% state of charge, confirming connectivity with the SmartShunt and Raspberry Pi's communication with the VRM Portal. The Garmin sensor for speed is also verified.

The routing for each trip follows the pre-defined route, only stopping for normal traffic conditions. Upon completion for a trip, data is checked for storage on both the Garmin and Victron platforms. The battery is rested and recharged in preparation for the next trip.

A Python script is developed to automate the processing of raw data into an organized format. The process is divided in four different categories: battery data processing, Garmin data processing, merging datasets into one spreadsheet, and finally appending the single trip data to a master file containing all trips. These processes are discussed in the following sub-sections, for which Python scripts are developed to automate the integration process, reducing the potential for manual errors and increasing efficiency.

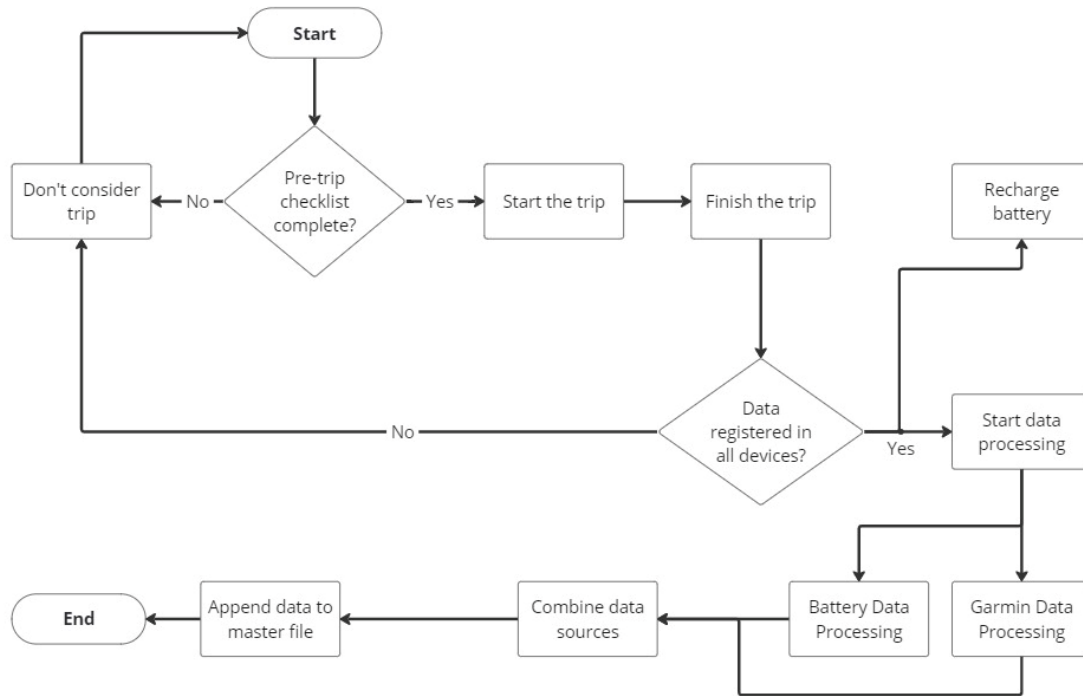


Figure 10: Data Collection Process

3.1.3.1. Battery Data Processing

The Python script for the battery data is designed to process and analyze data from a CSV file. The file generated by the battery monitor contains 45 columns with information about the system, errors, alarms and battery parameters. For the purpose of this project, only the following columns of interest related to battery monitoring were considered: timestamps, voltage, current, consumed amp-hours, state of charge and discharged energy.

The timestamp column is converted into a datetime format, and the other columns are converted into numeric types. Additionally, the timestamp column was corrected to account for the battery monitor recording time that was one hour ahead of the actual time. Given that the battery monitor updates only upon changes in various parameters, which could span from a second to a minute, the data is subsequently resampled to a consistent one-second frequency to maintain uniform time intervals. This resampling is followed by linear interpolation to fill in any gaps in the data.

The script also refines the dataset by renaming columns for enhanced clarity and splits the timestamp into separate date and time columns to facilitate more precise analysis. It then rearranges these columns, along with the battery parameters, in chronological order to establish a more organized structure. The finalized dataset is subsequently exported and saved as an Excel file.

3.1.3.2. *Garmin Data Processing*

The Python script for the Garmin data is designed to process data from the Garmin device. It starts by importing necessary libraries including 'fitparse' for parsing .fit files, 'pandas' for data manipulation, 'pytz' for time zone handling, and 'numpy' for performing mathematical and logical operations. The script defines paths for input .fit file, an output Excel file, and an input Excel file containing route data. It then loads the .fit file and initializes a dictionary to store various data fields like date, time, latitude, longitude, distance, speed, and temperature.

The script features a function that transforms latitude and longitude from semicircles into degrees. For every entry in the .fit file, it converts the timestamp to Toronto time zone, while also pulling data for each specific field. Additionally, the script changes the speed measurements from meters per second to kilometers per hour.

A custom function processes the data to filter out stationary periods at the beginning and end of the data. The start of a trip is defined when the distance measurement transitions from zero to a positive value, indicating the commencement of movement. Conversely, the trip ends when the speed reduces to zero and remained unchanged until the final recorded data point.

While the Garmin device captured elevation data, inconsistencies were noted for the same route across various trips, attributed to variations in slope calculations, weather effects, GPS precision, and trip-specific variations. To achieve uniform elevation data for accurate slope estimation, a new method was employed. Using ArcGIS Pro, coordinates were extracted at 5-meter intervals along the route, including the endpoint, and consolidated into an Excel spreadsheet. A Python script, leveraging pandas and the Google Maps libraries, was crafted to augment this dataset with elevation details from the Google Maps Elevation API. This script added elevation information to each point and computed the average slope by averaging the elevation differences from the lowest to the highest points.

Finally, the script reorders the columns in chronological order and saves it as an Excel file.

3.1.3.3. *Datasets Merging*

This Python script merges the battery and Garmin datasets into a single, unified dataset. It begins by importing essential libraries like pandas, numpy, and openpyxl. Additional information is added manually, including the rider weight, extra weight, assistance level, and bike specifications.

After the merging process, the script enhances the dataset by introducing new columns that incorporate details such as the bike model, motor power, torque, battery capacity, and various weights.

The script introduces a tailored function designed to compute the rates of key variables: state of charge, voltage (V), current (A), discharged energy, and consumed amp-hours. This approach aims to enhance the consistency of these variables, providing a broader range of comparison options for the analysis.

Any gaps in the data are filled with default values (e.g., 0) for consistency. Finally, the cleaned and combined dataset is saved to a new Excel file.

3.1.3.4. Data Consolidation

The final Python script compiles data by appending the files from each trip, produced during the datasets merging process, into a comprehensive master file in Excel format.

3.2. Data Attributes

The final dataset resulting from the data collection process is presented in Table 10. Each variable measures a characteristic of the cycling experience and the performance of the ECC.

Table 10: Processed Dataset Variables

Variable	Unit	Description
Date	Date	Date of data collection
Time	Time	Time of data recording
Model	Brand / Model	Name or designation of the ECC
Latitude	Decimal Degrees	Geographical latitude
Longitude	Decimal Degrees	Geographical longitude
Distance	m	Total distance covered during the activity
Motor power	W	Maximum power output of the motor
Torque	Nm	Rotational force of the motor
Battery capacity	Wh	Total energy storage capacity of the ECC's battery
ECC weight	Kg	Weight of the ECC
Rider weight	Kg	Weight of the rider
Extra weight	Kg	Additional weight carried by the rider
Total weight	Kg	Total combined weight (Rider + Extra Weight)
Assistance level	Level	Level of electronic assistance provided by the motor
Speed	m/s km/h	Cycling speed in meters per second in kilometers per hour
Average slope	-	Average incline or decline of the path
Temperature	°C	Ambient temperature
Voltage	V	Battery voltage
Voltage rate	V/m	Average rate of the voltage

Variable	Unit	Description
Current	A	Battery current draw
Current rate	A/m	Average rate of the current
Consumed amp-hours	Ah	Amount of electrical charge consumed
Consumed amp-hours rate	Ah/m	Average rate of the consumed amp-hours
State of charge (SoC)	%	Percentage of battery charge remaining
SoC rate	%/m	Average rate of the SoC
Discharged energy	kWh	Total energy discharged from the battery
Discharged energy rate	kWh/m	Average rate of the discharged energy

The *date and time* variables capture the date and time at which each trip was recorded, with data points collected at a frequency of one second. Additional variables are gathered by the Garmin device, including *latitude, longitude, distance, speed, and temperature*.

A subsection of the variables measured for the ECCs are static and do not change during testing. These attributes include the *model*, along with some specifications of the ECC, including the *motor power, torque, and battery capacity*.

A few variables vary for each trip but do not change during observations within a trip. This includes the *total weight*, which is composed of the *ECC weight*, the *rider's weight*, and *extra weight*. The latter variable represents the additional load placed on the ECC for each trip to represent cargo. Similarly, the *assistance level* stays consistent during each test run, adhering to the predefined level set for the data collection scenario.

Average slope is included within the dataset as part of the process explained in Section 3.1.3.2.

Battery-related attributes, including *voltage, current, consumed amp-hours*, and *state of charge (SoC)*, reflect battery performance during trips. *Voltage* is the force that propels electricity from the battery, while *current* refers to the flow of electrical charge from the battery to the motor. The *SoC* indicates the remaining capacity of the battery. *Discharged Energy* measures the energy drawn from the battery, but the battery monitor accumulates values, causing subsequent trips to start with the ending value of the previous trip.

The variation in certain variables offers a clearer insight into battery performance. Consequently, the rate or slope of the graph for variables such as *voltage, current, consumed amp-hours, state of charge (SoC), and discharged energy* is calculated, using *distance (m)* as the denominator.

3.3. Outlier Analysis

The final dataset is processed to identify and remove outliers. Initially, outliers for each variable are identified using the interquartile range (IQR), which calculates the spread between the 75th (Q3) and 25th (Q1) percentiles. A data point is considered an outlier if it is below the lower boundary ($Q1 - 1.5 * IQR$) or above the upper boundary ($Q3 + 1.5 * IQR$). Upon identifying outliers, they are evaluated for removal based on whether they reflect an incongruency with known conditions, in which case the entire data point is removed.

3.4. Summary Statistics

Following the data cleaning process, the summary statistics of the final dataset are calculated. This summary provides insights into the dataset through various measures:

- Ct. (Count): The total number of observations for each attribute, indicating the dataset's size.
- Uq. (Unique): The diversity of values within each attribute, highlighting the range of different values present.
- Mean: The average value across observations for each attribute, offering a central point around which data points are distributed.
- Std (Standard Deviation): This quantifies the variation or spread of the data points around the mean. A larger standard deviation signifies more dispersion within the dataset.
- Min: The lowest value within each attribute, marking the minimum observed data point.
- 25% (First Quartile): The value below which 25% of the observations fall, indicating the lower quartile of the dataset.
- Median: The middle value when observations are arranged in ascending order, providing a robust measure of central tendency less influenced by outliers.
- 75% (Third Quartile): The value below which 75% of observations fall, marking the upper quartile of the dataset.
- Max: The highest value within each attribute, indicating the maximum observed data point.
- Sk (Skewness): This assesses the asymmetry of the distribution. Positive skewness indicates a distribution with a tail extending towards higher values, while negative skewness points to a tail stretching towards lower values.
- K (Kurtosis): This measures the sharpness or flatness of the distribution. A high kurtosis value denotes a more peaked distribution, whereas a low kurtosis suggests a flatter shape.

3.5. Linear Correlations

A Pearson correlation analysis is conducted next to assess the linear correlations between variables. The Pearson correlation coefficient, or Pearson's r , measures the linear correlation between two variables X and Y . It has a value between +1 and -1, where 1 is total positive linear correlation, 0 is no linear correlation, and -1 is total negative linear correlation.

Eq. (1) shows the Pearson correlation coefficient.

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}} \quad \text{Eq. (1)}$$

Where:

- r is the Pearson correlation coefficient,
- X_i and Y_i are the individual sample points indexed with i ,
- $\bar{X}$ and $\bar{Y}$ are the means of the X and Y variables.

Pearson's r is widely used in the fields of statistics, finance, physical sciences, and social sciences to measure the strength and direction of a linear relationship between two variables. However, it's important to note that Pearson's r only measures linear relationships and may not accurately represent the strength of non-linear relationships (Mendenhall & Sincich, 2015).

To assess the statistical significance of the Pearson's r , a t-test is included using Eq. (2).

$$t = r \sqrt{\frac{n-2}{1-r^2}} \quad \text{Eq. (2)}$$

Where:

- r is the Pearson correlation coefficient,
- n is the number of pairs of data,
- t is the test statistic which follows a t-distribution with $n-2$ degrees of freedom.

A small p-value (<0.05) indicates that the correlation is statistically significant with 95% confidence and rejecting the null hypothesis that there is no correlation. When creating the Spearman correlation matrix, values with a correlation less than -0.5 or greater than 0.5, along with a p-value less than 0.05.

3.6. Non-Linear Correlations

The initial data analysis, discussed later in Chapter 4 indicated substantial non-linear relationships and, therefore requires an alternative method to determine the correlation among the different

variables. The Spearman correlation is a non-parametric measure of rank correlation. The Spearman correlation ranks the data points from each variable separately and then calculates the correlation coefficient based on these ranks rather than on the raw data. This approach makes it suitable for use with non-linear relationships and data that does not follow a normal distribution (Siegel & Castellan Jr., 1988).

The Spearman rank correlation coefficient, denoted as ρ (rho) or sometimes as r_s , is calculated using Eq. (3).

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad \text{Eq. (3)}$$

Where:

- $\sum d_i^2$ is the sum of the squares of the rank differences between paired observations,
- d_i is the difference in ranks for each pair of observations,
- n is the number of observations.

The resulting ρ value will always occur between -1 and 1. A positive correlation indicates that the value of one variable increasing will tend to coincide with an increase for the other variable. A negative correlation indicates that the value of one variable increasing will likely coincide with a decrease for the other variable. A larger value towards 1 or -1 indicates a stronger relationship. A value of 0 implies no identified correlation.

To assess the statistical significance of the Spearman's correlation, a t-test will be conducted, following Eq. (4).

$$t = \rho \sqrt{\frac{n - 2}{1 - \rho^2}} \quad \text{Eq. (4)}$$

Where:

- ρ is the Spearman rank correlation coefficient,
- n is the number of pairs of data,
- t is the test statistic which follows a t-distribution with $n-2$ degrees of freedom.

A small p-value (<0.05) indicates that the correlation is statistically significant with 95% confidence and rejecting the null hypothesis that there is no correlation. When creating the Spearman correlation matrix, values with a correlation less than -0.3 or greater than 0.3, along with a p-value less than 0.05.

3.7. The Electric Cargo Cycle Battery (ECCB) Model

3.7.1. Model Selection

Several models that do not rely on linearity are considered herein to represent the relationship between ECC usage and battery performance. This encompasses approaches such as polynomial regression and machine learning methodologies such as neural network and random forest. These latter techniques are particularly useful to model complex relationships present within large datasets.

When comparing between polynomial regression, neural network, and random forest for model selection, several parameters and criteria should be considered to determine the most suitable approach. These criteria encompass model complexity, interpretability, prediction accuracy, computational efficiency, and the nature of the data. Table 11 shows a comparative analysis of polynomial regression, random forest, and neural network across the different parameters.

Table 11: Comparative Analysis of the Considered Methodologies

Parameter	Polynomial Regression (Zach, 2020)	Random Forest (Fox, et al., 2020; IBM, 2024)	Neural Network (Alzubaidi, et al., 2021)
Model Complexity and Flexibility	Simple and less flexible, complexity increases with the degree.	Flexible, aggregates multiple decision trees, less prone to overfitting.	Highly flexible, can model very complex relationships.
Interpretability	More interpretable, direct relationship between predictors and output.	Individual trees are interpretable, the ensemble less so.	Often considered as "black boxes" due to complex structure.
Prediction Accuracy	Less effective at capturing complex patterns, might have lower accuracy.	Strong performance, robust to overfitting, effective on various datasets.	Capable of high accuracy on large and complex datasets.
Computational Efficiency	Computationally efficient for lower-degree polynomials.	Intensive with a large number of trees, but often faster than neural network.	Requires significant computational resources and optimization.
Data Requirements and Preprocessing	Requires variable selection and preprocessing, sensitive to outliers.	Handles a wide range of data types, less sensitive to data scale, handles missing values.	Extensive preprocessing needed, benefits from large datasets.

Polynomial Regression (PR) is simple and less flexible, becoming more complex with increasing degree, and while it's computationally efficient for lower degrees, it struggles with complex patterns and requires careful variable selection, being sensitive to outliers (Zach, 2020).

Random Forest (RF) is more flexible, combining multiple decision trees to build a model that is less likely to overfit and robust across different datasets; although individual trees are

interpretable, the ensemble as a whole is not as clear. They are computationally intensive but generally faster than neural network and handle a variety of data types, including missing values (Fox, et al., 2020; IBM, 2024).

Neural Network (NN) is the most flexible, modeling very complex relationships and offering high accuracy on large, complex datasets, but they're seen as "black boxes" due to their intricate structures and require significant computational power and extensive preprocessing (Alzubaidi, et al., 2021).

3.7.1.1. Polynomial Regression (PR)

Polynomial regression is a form of non-linear regression in which the relationship between the independent variables x and the dependent variable y is modeled as an n th degree polynomial (Zach, 2020).

$$y = \beta_0 + \beta_1x + \beta_2x^2 + \beta_3x^3 + \dots + \beta_nx^n + \epsilon \quad \text{Eq. (5)}$$

Where:

- y is the dependent variable,
- x is the independent variable,
- $\beta_0, \beta_1, \beta_2, \beta_3, \dots, \beta_n$ are the coefficients of the model (parameters),
- n is the degree of the polynomial,
- ϵ is the error term, which is the part of y that cannot be explained by the polynomial model of x .

3.7.1.2. Random Forest (RF)

Random Forest is an ensemble learning method used for classification and regression that operates by constructing a multitude of decision trees during training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees (IBM, 2024).

Random Forest involves the following steps and components (Nvidia, 2024):

- **Bootstrapping:** A Random Forest is built upon the concept of bootstrap aggregation, or bagging. For each tree in the forest, a bootstrap sample is drawn. This means a sample is taken from the original data with replacement, so each sample can be drawn more than once. This sample is typically about two-thirds of the original data set, and the remaining one-third is known as the out-of-bag (OOB) data which can be used for validation purposes.

- **Random Variable Selection:** When growing each tree, at each split in the tree, only a random subset of the variables is considered. The randomness in variable selection adds to the diversity among the trees in the model, which results in a lower correlation between trees and hence a higher robustness.
- **Tree Construction:** Each tree is grown to the maximum depth possible without pruning, meaning that it continues until each node is pure (i.e., all the training examples at the node are of the same class) or contains less than a minimum number of points.
- **Aggregation:** For regression tasks, the final prediction is typically the average of the predictions of all trees in the forest. For classification, it is a majority vote (mode) of the predictions.

Each decision tree D_i in the Random Forest makes a prediction Y_i based on its learned structure from the bootstrapped data. The final prediction $\hat{Y}$ for a given input X in regression is the average of the predictions of all individual trees (Hastie, et al., 2009; Breiman, 2001)

$$\hat{Y}(X) = \frac{1}{N} \sum_{i=1}^N Y_i(X) \quad \text{Eq. (6)}$$

Where N is the number of trees in the forest.

The OOB error is an estimate of the prediction error for each tree using the OOB data that was not included in the bootstrap sample. It provides a way to estimate the test error without needing a separate validation set or cross-validation.

Random Forest aims to build many uncorrelated trees to decrease the variance without increasing the bias too much. This is based on the principle that a group of weak learners can come together to form a strong learner.

Random Forest does not have coefficients like linear models do. Instead, it provides a measure of variable importance, which can be interpreted as how important a variable is when making predictions. This isn't the same as a coefficient in regression, but it gives an idea of which variables are contributing most to the prediction (Li, et al., 2019). This research used the methodology proposed by Scikit Learn (2024a) to identify the variable importance for the Random Forest model.

Random Forest are popular due to their simplicity, ease of use, and ability to handle a variety of data types, including both numerical and categorical data. They are also robust to outliers and scalable to large datasets (IBM, 2024).

3.7.1.3. Neural Network (NN)

A neural network is a computational model inspired by the way biological neural network in the human brain process information. It is composed of a large number of interconnected nodes, or "neurons," which work together to solve complex problems (Alzubaidi, et al., 2021).

Neural network involves the following steps and components:

- Input Layer: The layer that receives the input signal to be processed.
- Hidden Layers: One or more layers where computation and transformation of the input signal take place.
- Output Layer: The layer that produces the final output of the network.

Each neuron in one layer is connected to neurons in the next layer through pathways. The strength of these connections is represented by weights, which are adjusted during the training process.

A popular method to generate NN models is using forward propagation, where each neuron receives inputs from the previous layer, which are multiplied by the weights on the connections. The weighted inputs are summed together, typically with a bias term added. An activation function is applied to this sum to produce the neuron's output (Scientist Cafe, 2024).

$$a^{[l]} = g^{[l]}(W^{[l]}a^{[l-1]} + b^{[l]}) \quad \text{Eq. (7)}$$

Where:

- $a^{[l]}$ is the activation of the l -th layer,
- $W^{[l]}$ and $b^{[l]}$ are the weights and biases for the l -th layer,
- $g^{[l]}$ is the activation function for the l -th layer.

Common activation functions include the sigmoid, tanh, ReLU (Rectified Linear Unit), and softmax functions. These functions introduce non-linear properties to the network, allowing it to learn more complex representations. For this research, ReLU is the activation function used since it allows faster training (Scikit Learn, 2024b).

The loss function evaluates the performance of the neural network. Common loss functions include Mean Squared Error (MSE) for regression tasks and cross-entropy loss for classification tasks (Scikit Learn, 2024b).

Backpropagation is used to calculate the gradient of the loss function with respect to each weight in the network. This involves applying the chain rule of calculus to compute gradients for each layer from the output layer backward to the input layer (Kostadinov, 2019).

$$W^{[l]} := W^{[l]} - \alpha \frac{\partial L}{\partial W^{[l]}} \quad \text{Eq. (8)}$$

Where:

- α is the learning rate,
- L is the loss function.

Various optimization algorithms can be used to update the weights, such as Gradient Descent, Stochastic Gradient Descent (SGD), Adam and RMSprop. These algorithms aim to minimize the loss function by adjusting the weights and biases of the network. For this research, the Adam optimization algorithm is used since it is more efficient in terms of both training and validation score (Scikit Learn, 2024b).

To prevent overfitting, techniques like L1 and L2 regularization, dropout, and early stopping are used. Regularization modifies the loss function or network architecture to reduce complexity. For this research, L2 with an alpha value of 0.0001 is used. This penalty encourages the weights to be small and don't prevent the model from learning complex patterns in the data (Scikit Learn, 2024b).

Neural networks require a significant amount of data to train effectively and can be computationally intensive, but they have a high capacity for modelling complex, non-linear relationships (Alzubaidi, et al., 2021).

3.7.2. Model Evaluation

Throughout this thesis, the construction of these models utilizes a data partitioning approach with 20% of the data allocated for training and 80% reserved for testing, applicable across all datasets used.

The metrics selected to evaluate the built models include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2).

The Mean Absolute Error (MAE) represents the average of the absolute differences between the predicted and actual values. It provides a straightforward measure of prediction accuracy, with a value of 0 indicating no error. The model with the lower MAE value is usually preferred.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad Eq. (9)$$

Where:

- n is the number of observations,
- y_i is the true value,
- $\hat{y}_i$ is the predicted value.

The Root Mean Squared Error (RMSE) represents the square root of MSE. RMSE is in the same units as the response variable and is useful for understanding the magnitude of prediction errors. The model with the lower RMSE value is usually preferred.

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad Eq. (10)$$

The R-squared (R^2) metric represent the proportion of the variance in the dependent variable that is predictable from the independent variable(s). It provides a measure of how well observed outcomes are replicated by the model, based on the proportion of total variation of outcomes explained by the model. The model with the higher R^2 value is usually preferred.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad Eq. (11)$$

Where:

- $\bar{y}$ is the mean of the observed data.

Metrics such as the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC) will not be evaluated. Random Forest (RF) diverges from linear regression or generalized linear models in that they do not rely on likelihood functions in the same manner. The challenge with applying AIC and BIC to RF stems from RF's inability to produce estimates of parameter variance that adhere to specific distribution assumptions, a key component for AIC and BIC

calculations. While a model selection criterion akin to AIC/BIC for RF could be conceptualized, its applicability and comparability with RF would be limited (Piazza Resources, 2024; Tim, 2020).

3.7.3. Model Validation

To validate the accuracy of the model, the SoC of each ECC is calculated and then compared with the collected data. The values referenced in the next paragraphs are from the final dataset.

When considering *extra weight*, the ECCB model utilizes an average for each ECC scenario, based on the values for the two trips completed with loads of approximately 50 kg and 100 kg. For Ami, *extra weights* of 56.95 kg and 106.25 kg are used; for Babboe, the *extra weights* are 50.45 kg and 107.60 kg; and for the combined dataset, *extra weights* are 53.70 kg and 106.93 kg.

The *total weight* incorporates an average *rider weight* of 91.50 kg, plus the *ECC weight* of 90 kg for Babboe and 100 kg for Ami, along with the accounted *extra weight*.

Later analysis in Chapter 4 results in the adoption of *SoC rate* as the dependent variable for the ECCB model, which represents the battery consumption rate. The ECCB model is able to calculate the final SoC (y_2) by predicting the *SoC rate* (m) based on the distance travelled ($x_2 - x_1$) and the initial SoC (y_1) as shown in Figure 11.

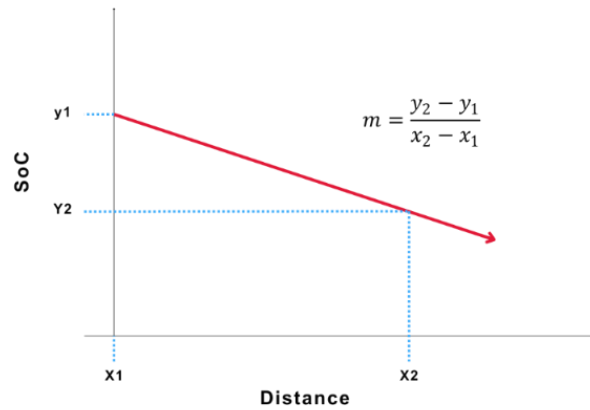


Figure 11: Slope Calculation Graph

Each ECC departs with a full charge, setting y_1 at 100%. A standard distance ($x_2 - x_1$) of 5 km is applied across all scenarios.

Eq. (12) is used to calculate the final SoC.

$$y_2 = m(x_2 - x_1) + y_1 \quad \text{Eq. (12)}$$

3.7.4. Sensitivity Analysis

A sensitivity analysis is conducted to validate the robustness and limitations of the ECCB model. The approach entails performing a sensitivity analysis on each independent variable within the datasets. Each variable is adjusted by up to +/- 100% from a baseline of 50 for the *extra weight* (0 kg – 100 kg); 170 for the *total weight* (0 kg – 340 kg), and 3 for the *assistance level* (0 - 5), in order to observe the impact of these variations on the predictive accuracy of the ECCB model.

3.8. The Electric Cargo Cycle Routing Problem (ECCRP) Model

The fourth objective of this study is to create a route optimization model that enhances battery efficiency, enabling them to visit the maximum number of customers with a specific ECC. The application of ECCs for route optimization introduces new complexities and considerations when compared to leisure cycling with no e-assist, such as the battery range and load capacity.

This section discusses into a base Electric Cargo Cycle Routing Problem (ECCRP) framework, considering the specific technical attributes of the ECCs. This model is later improved to incorporate the ECCB model as the Enhanced ECCRP (E-ECCRP).

For comparative purposes, the analysis assumes each ECC operates with a single battery (E-ECCRP-1). However, in practical applications, outfitting a single ECC with an additional battery to finish a route is a viable alternative. This consideration led to the introduction of a variant within the enhanced model that allocates two batteries per ECC (E-ECCRP-2).

The model is developed using OR-Tools by Google, which is an open-source software suite designed for optimization and constraint programming using Python, C++, Java and C# (Google OR-Tools, 2023). For this research, Python is the programming language used.

Table 12 shows the different variables considered in the different models. Details on how they are used in the model are in chapter 6.

Table 12: Set of Variables for Building the ECCRP and the E-ECCRP

Variable	Definition	Unit
Q	Battery Capacity	Wh
$L_{max,k}$	Battery Range	km
x_{ijk}	Binary Variable	-
m_{ijk}	Consumption rate (SoC rate) for k travelling from customer i to j .	-
i, j	Customers	-
c	Distance travelled (Cost)	km
k	ECC	-
y_{1k}	Initial SoC of k at the depot	%
LC_k	Load Capacity	kg
q_i	Demand at location i (positive for pickup, negative for delivery)	kg
V_{max}	Maximum speed	km/h
n	Set of customers	[1, 2, ..., n]
K	Set of ECCs (fleet)	[1, 2, ..., z]
SoC	State of Charge	%
y_{2ijk}	State of charge of k after travelling from customer i to j	%
u	Auxiliary variable representing the position in the tour	-
P_T	Motor power	W
V	Voltage	V

To identify the best solution, the ECCRP, the E-ECCRP-1 and the E-ECCRP-2 models, employed two sequential approaches. The initial strategy, known as *path cheapest arc*, builds a preliminary route by sequentially incorporating the shortest arc available. This preliminary outcome is then refined through the application of a metaheuristic known as Guided Local Search, which is considered an effective metaheuristic for vehicle routing tasks. This strategy aids in breaking free from local optima, enhancing the initial route. It targets aspects of the solution that pose optimization challenges and assigns penalties to promote the investigation of previously neglected parts of the solution space (Google Developers, 2023).

In the comparative study of the ECCRP, the E-ECCRP-1 and the E-ECCRP-2 models the depot is set at the York University Bookstore, with geographic coordinates at 43.774076, -79.501122. The analysis explored a series of cases for each ECC, with different coverage maximums, randomly placing 30 service points within a 5 km and 10 km radius of the depot to simulate a broad service area, as shown in Figure 12. The data information of the distribution of these service points is shown in Appendix B.

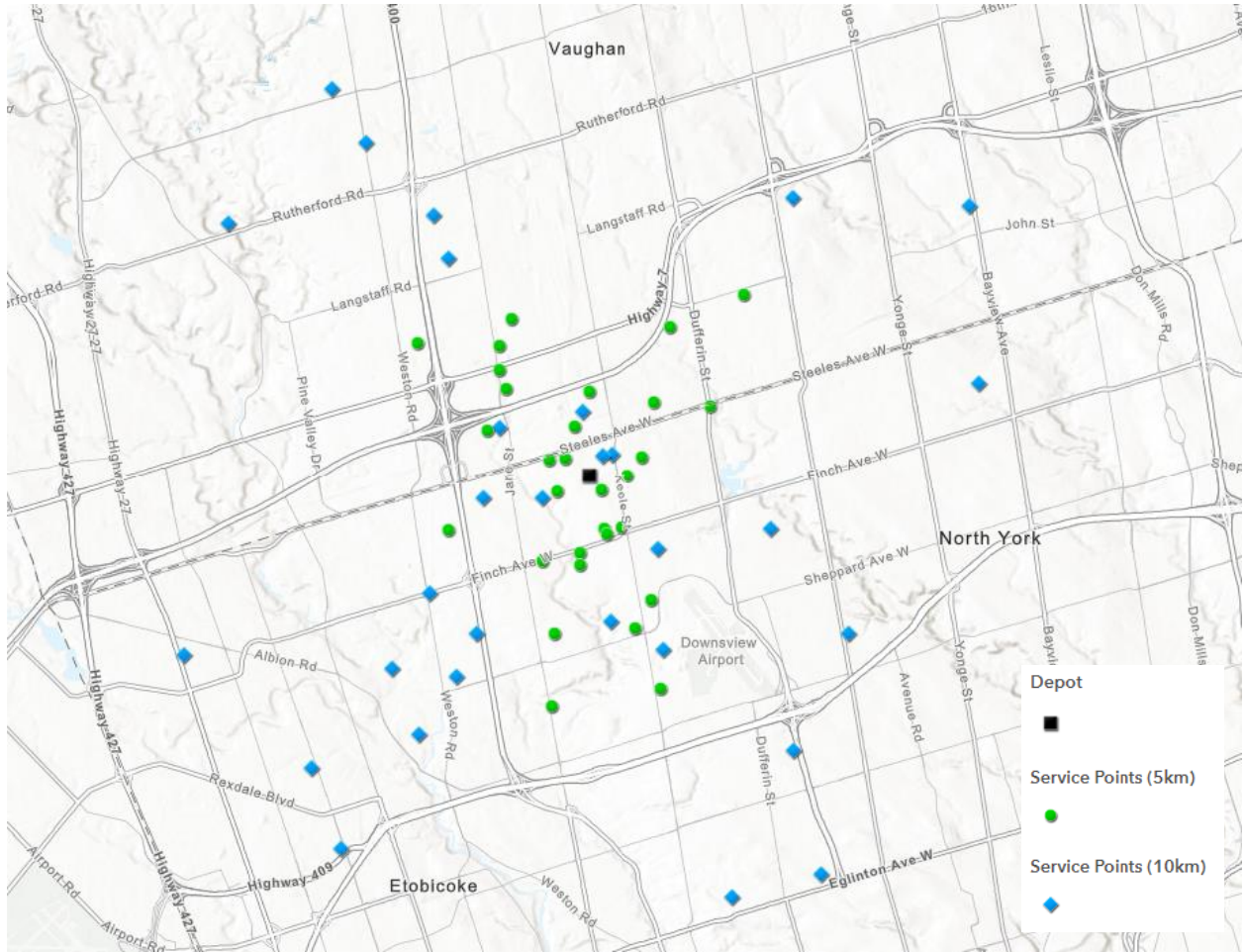


Figure 12: Distribution of Service Points Around the Depot

The nature of the service, either delivery or pickup, and the related service values for these customers is randomly generated within specified bounds for demand of 5 kg to 20 kg and 5 kg to 30 kg. The model does not evaluate the type of product because the crucial factor is the weight of the package, regardless of its shape. Furthermore, the E-ECCRP models are assessed across various operational conditions, including the *assistance level*, the initial SoC of the ECCs, and the *rider weight*.

In the analysis, ECCs are allocated a *rider weight* of 70 kg, approximating the mean weight of Canadians. Additionally, a scenario considering a *rider weight* of 100 kg is explored to encompass individuals who may fall into the overweight category. As reported by the World Population Review (2024), the average Canadian stands at 5 feet 10 inches tall (1.78 meters). Statistics Canada (2023) data indicates that a Body Mass Index (BMI) within the normal range (18.5 to 24.9)

corresponds to a weight spectrum from approximately 58.64 kg to 78.93 kg. For those classified as overweight, weight may rise to 94.78 kg.

When considering the *assistance level* for the E-ECCRPs, the battery range shifts according to the assistance value provided. Since there's no direct data to establish this correlation, it's assumed that the highest *assistance level* equates to the minimum battery range, while the lowest *assistance level* corresponds to the maximum battery range. This assumption led to the derivation of an intermediate value for *assistance level* 3 across for Ami (33 km) and Babboe (58 km) to ensure equitable comparison of results. Efforts to gather specific details from Babboe and Cycles Toussaint were unfruitful, as these parameters largely depend on the motor's integration with the ECC's battery system, a detail not specified in technical manuals. Consequently, an average of the technical specifications' upper and lower battery range limits is considered to address this gap. This approach underscores the complexities in quantifying *assistance levels* due to variations in ECC and the nature of the motor and battery integrations.

Optimization scenarios 1 and 7 serve as the baseline for comparison for service points at 5 km and 10 km from the depot, respectively. The cells shaded in grey in Table 13 indicate the specific elements that differ from the baseline scenarios.

Table 13: Optimization Scenarios

Scenario	No. Customers	Max distance (km)	Max demand (kg)	Assistance Level	Initial SoC (%)	Driver's Weight (kg)
1	30	5	20	4/5	100	70
2	30	5	30	4/5	100	70
3	30	5	20	3	100	70
4	30	5	20	4/5	80	70
5	30	5	20	4/5	50	70
6	30	5	20	4/5	100	100
7	30	10	20	4/5	100	70
8	30	10	30	4/5	100	70
9	30	10	20	3	100	70
10	30	10	20	4/5	80	70
11	30	10	20	4/5	50	70
12	30	10	20	4/5	100	100

3.9. Chapter Summary

This chapter outlines the research methodology applied to gather and analyze data for this thesis, conducted at the York University's Keele Campus. Centered around the Bergeron Centre for

Engineering Excellence, the selected route spans approximately 5 kilometres, offering a varied urban environment including mixed traffic conditions, varying slopes, and pedestrian zones. The study utilized two different Electric Cargo Cycle (ECC) models, the Ami Trishaw and the Babboe Pro Trike XL Midmotor, each outfitted with an array of data collection tools including the SmartShunt battery monitor, Raspberry Pi 4, and Garmin Edge 530, to accurately track and record the vehicle's trajectory and performance metrics.

Data was gathered between September 27 and December 22, 2023, culminating in 46 successful trips that collectively covered a distance of 230 km. The study tested different cargo loads and battery assistance levels, capturing a wealth of data points at one-second intervals that encompass speed, temperature, and battery efficiency among other variables. The dataset comprises detailed records spanning date, time, geographical coordinates, total weight, assistance level, and various battery performance indicators such as voltage, current state of charge and consumed amp-hours. This facilitated a comprehensive analysis, incorporating outlier detection and summary statistics to distill insights from the data, alongside a thorough examination of both linear and non-linear variable correlations to unveil the complexities of ECC operation.

Further, the development of the Electric Cargo Cycle Battery (ECCB) model is discussed, illustrating the selection process between polynomial regression, random forest, and neural network based on criteria such as model complexity, accuracy, applicability, and statistical analysis. This exploration underscores the nuanced decision-making behind the ECCB model formulation and its subsequent evaluation.

Lastly, the chapter introduces the Electric Cargo Cycle Routing Problem (ECCRP) framework and its evolution into the Enhanced ECCRP (E-ECCRP), aiming to optimize route efficiency within the constraints of battery range. Utilizing Google's OR tools, the model seeks to enhance the practical application of ECCs by maximizing the number of customer visits under varied operational conditions. This comprehensive approach not only demonstrates the methodological rigor of the study but also highlights the multifaceted considerations inherent in optimizing ECC performance for urban logistics.

4. Data Analysis

This chapter delves into the analysis of electric cargo cycle (ECC) performance, leveraging a rich dataset encompassing two models: Ami and Babboe. Through examination of raw data, outlier identification, and the application of both linear and non-linear statistical methodologies, it aims to decode the dynamics affecting operational efficiency and battery utilization under a variety of conditions. This analysis not only lays a critical foundation for understanding ECC functionality in diverse operational scenarios but also emphasizes the need for advanced analytical techniques to accurately forecast performance outcomes and optimize ECC efficiency, providing a comprehensive overview of their capabilities and limitations within the context of sustainable urban mobility.

4.1. Raw Data Overview

Analyzing the data as collected reveals a generic understanding on some of the variables.

Figure 13 and Figure 14 show Ami and Babboe operating at different *assistance levels*, respectively. This includes level 1 (L1), level 3 (L3) and level 5 (L5) for Ami, and level 1 (L1), level 3 (L3) and level 4 (L4) for Babboe. Both figures reveal that each model exhibits comparable *speed* ranges, with *speed* increasing alongside higher *assistance level*, especially in Ami. The SoC demonstrates a larger decrease as *assistance levels* increase, a trend also observed with consumed amp-hours. Ami registers a lower SoC compared to Babboe. *Voltage* and *current* display considerable fluctuations throughout the journey in both models but clearly maintaining higher *voltage* levels at lower *assistance levels* is noticeable.

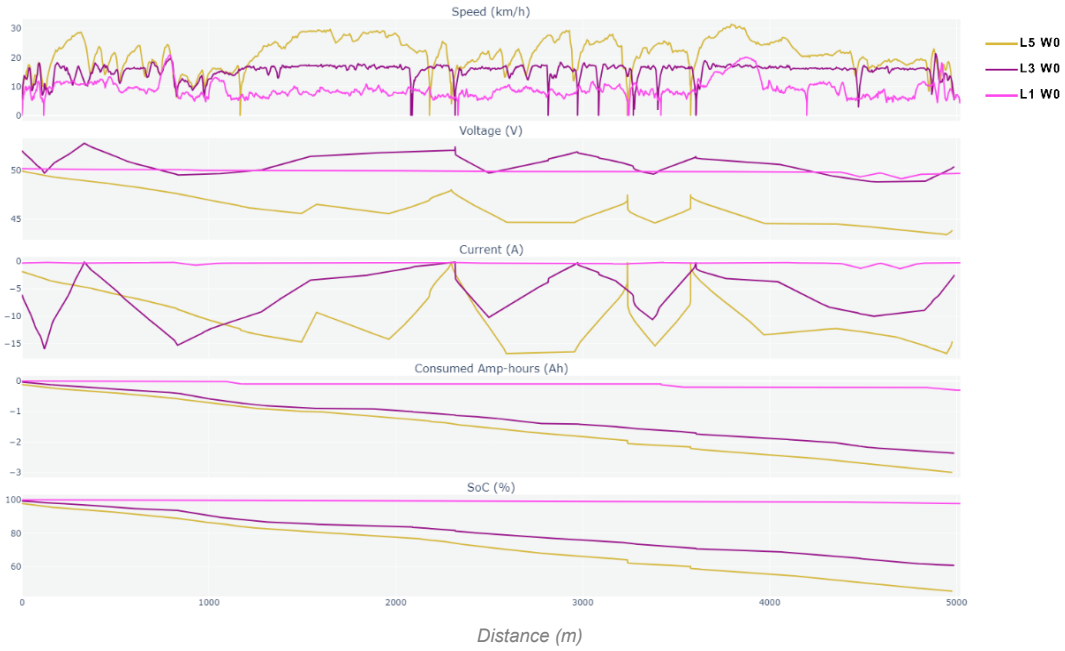


Figure 13: Ami Data Comparison by Assistance Level

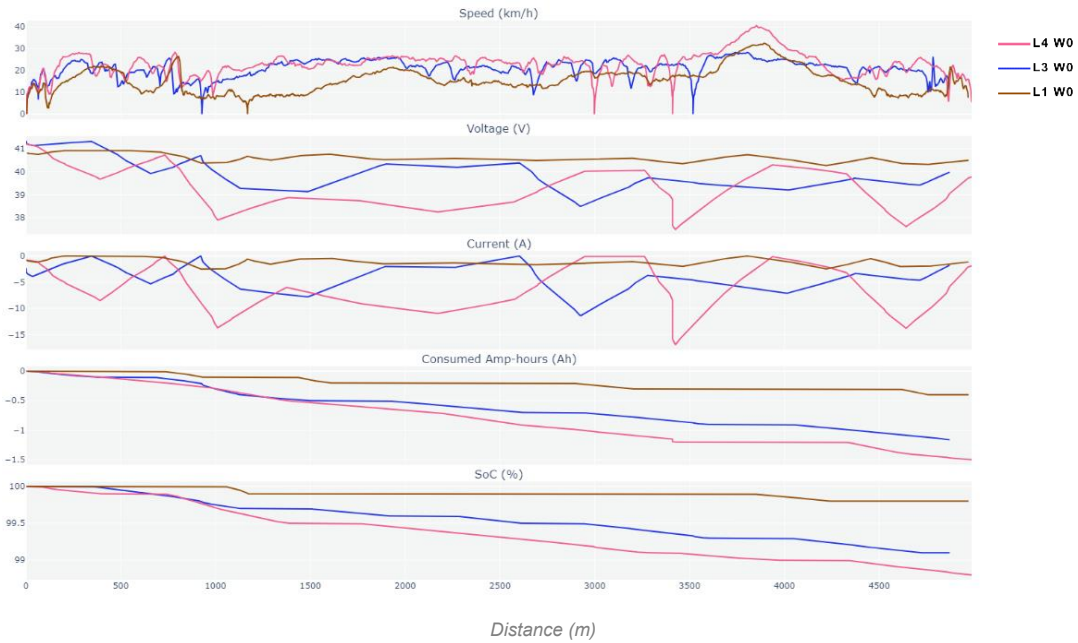


Figure 14: Babboe Data Comparison by Assistance Level

Figure 15 and Figure 16 present Ami and Babboe under different *extra weight* conditions, respectively. In these figures, both ECCs exhibit a broader *speed* range with Babboe showing a higher range; however, *speed* decreases as the *extra weight* increases. For both models, an

increased *extra weight* correlates with a steeper SoC decline, with Ami's minimum SoC around 45% and Babboe is around 98.5%. Similar patterns are observed in *consumed amp-hours*, while *voltage* and *current* lack a consistent trend across the route.

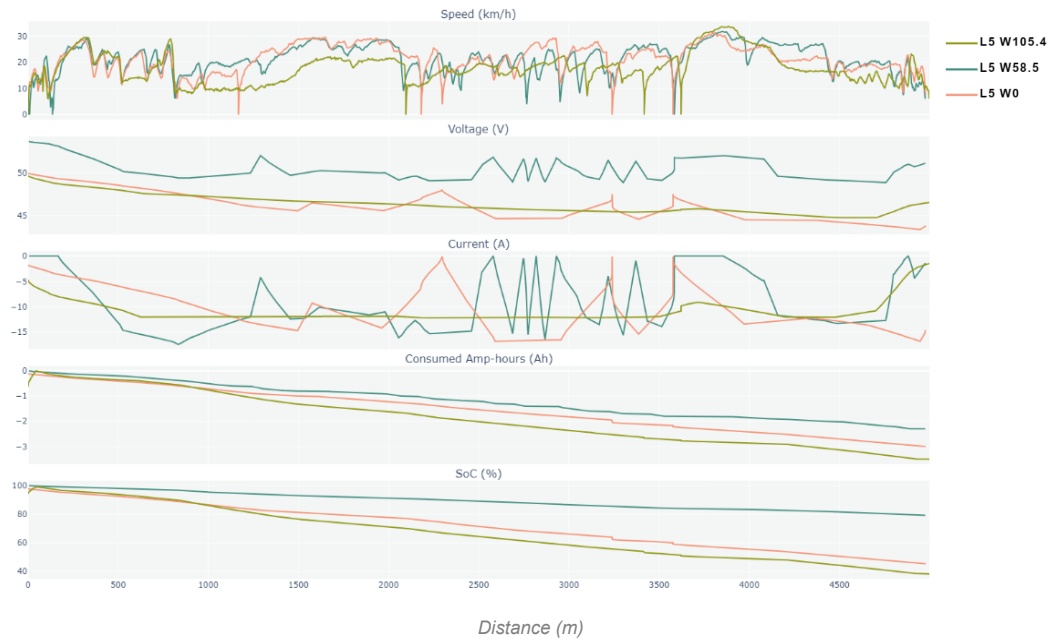


Figure 15: Ami Data Comparison by Extra Weight

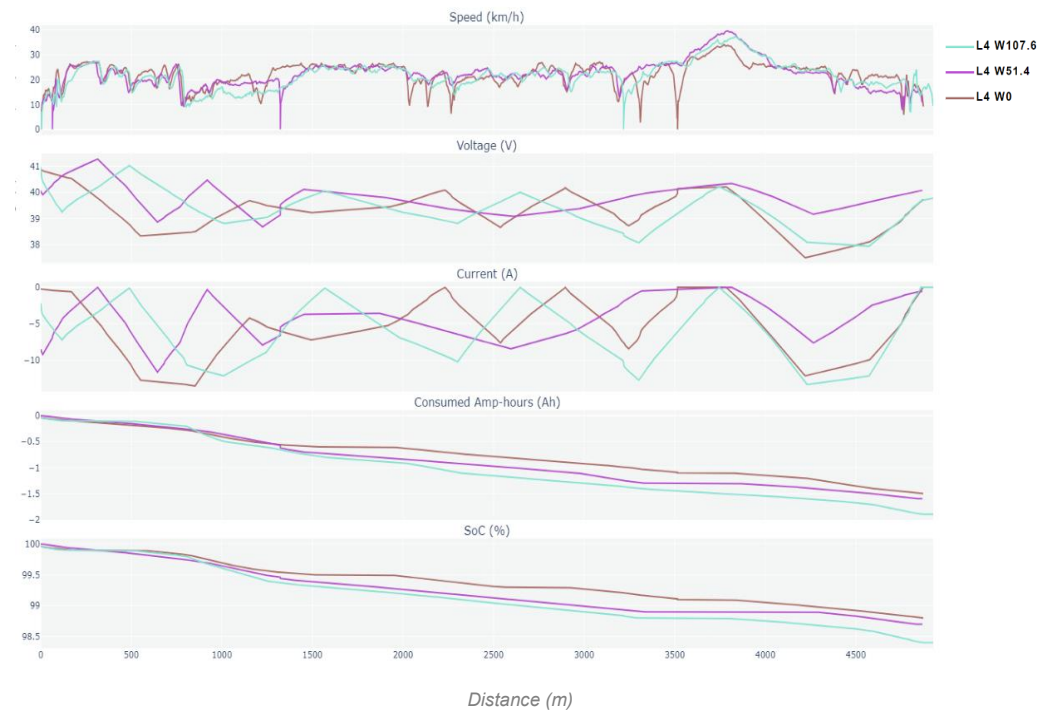


Figure 16: Babboe Data Comparison by Extra Weight

Figure 17 compares Ami and Babboe at the lowest *assistance level* with no *extra weight*. This comparison indicates that Babboe tends to be faster probably due to multiple factors like the weight of the vehicle, since it is lighter than Ami, and more powerful battery assistance. Babboe also has a higher value of SoC due to a lower *SoC rate*. Ami exhibits higher *consumed amp-hour*, *voltage* and *current* levels.



Figure 17: Ami vs Babboe Under the Same Conditions

These observations suggest that *assistance level* and *extra weight* can affect battery performance, with both factors contributing to a quicker SoC depletion in both ECCs. Babboe demonstrates superior battery performance compared to Ami.

4.2. Outlier Analysis

Figure 18 displays box and whisker plots for the dataset's variables, excluding those lacking variability such as *motor power*, *torque*, *battery capacity*, *rider weight*, *extra weight*, *total weight*, *assistance level* and *distance*, as well as those variables not prone to outliers, such as *date*, *time*, *latitude*, *longitude*, *distance*.

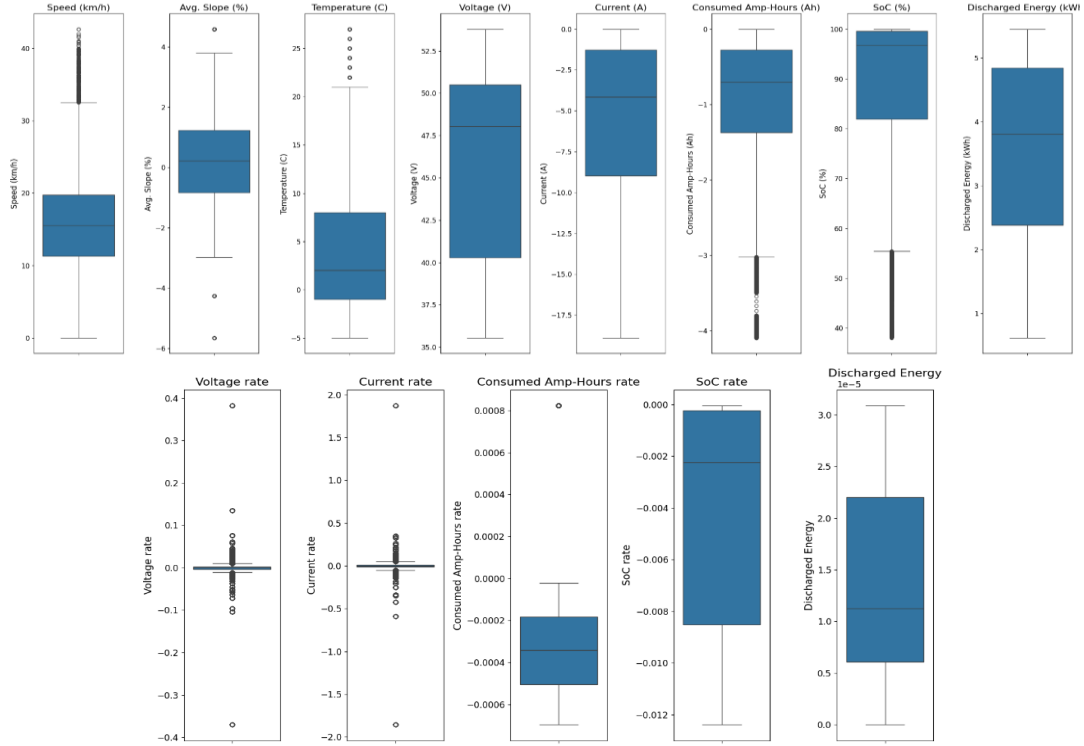


Figure 18: Box and Whisker Plots of the Combined Dataset

The *State of Charge (SoC)* exhibits outlier values ranging from 38% to 55.4% at the lower end, predominantly during the use of the highest, energy-intensive assistance level. Similarly, Consumed Amp-hours showed low outliers between -3.02 Ah to -4.10 Ah during the most power-demanding *assistance level* setting. No outliers are identified in *voltage, current, discharged energy, SoC rate and discharged energy rate* readings; however, *consumed amp-hours, consumed amp-hours rate, voltage rate and current rate* presented outliers.

Given the critical importance of battery-related variables in this research and the lack of errors from the battery monitor during the trips, outliers within battery-related variables are being retained.

Outliers identified for the *speed* range between 32.55 km/h and 42.66 km/h, are noted primarily at the highest assistance levels and on downhill segments of the route. This is more prominent for Babboe, which is recognized in the previous section as the faster vehicle.

The statistical outliers for *speed, voltage, voltage rate, current, current rate, consumed amp-hours, consumed amp-hours rate, SoC, SoC rate, discharged energy and discharged energy rate*

are logically plausible within the context provided and don't present any errors. For that reason, they are not removed from the dataset.

The data points that contained the statistical outliers for *temperature and average slope* were removed from the dataset. Outliers identified for the *average slope* range between as -4.26% and 4.59%, highlight the route's natural terrain variations, with a notable -5.66% *average slope* exclusively associated with Ami, an anomaly given the identical route shared between models. *Temperature* outliers are recorded between 22°C to -27°C on October 17, 2023, and 22°C to -23°C on November 13, 2023. These observations for the two dates diverge from the maximum recorded temperatures of 17 °C and 14 °C, respectively, reported by the Government of Canada (2024) for these dates. The majority of these *temperature* readings, occur on sunny days and subsequently influenced by the Garmin Edge 530 registering elevated temperatures when exposed to direct sunlight (Garmin, 2024).

Following the removal of 552 outlier data points, there are 51,359 data points retained for further analysis.

4.3. Summary Statistics

Following the data cleaning process, the summary statistics of the final dataset is calculated and presented below in Table 14. A description of each column is given in section 3.4.

Table 14: Summary Statistics of the Combined Dataset

Variable	Ct.	Uq.	Mean	Std	Min	25%	Median	75%	Max	Sk	K
Date	51359	20	-	-	-	-	-	-	-	-	-
Time	51359	30417	-	-	-	-	-	-	-	-	-
Model	51359	2	-	-	-	-	-	-	-	-	-
Latitude	51359	36163	-	-	-	-	-	-	-	-	-
Longitude	51359	40372	-	-	-	-	-	-	-	-	-
Distance	51359	47236	2444.72	1447.12	0	1149.59	2425.16	3605.25	5031.96	0.05	-1.19
Motor power	51359	2	-	-	250	-	-	-	500	-	-
Torque	51359	2	-	-	45	-	-	-	70	-	-
Battery capacity	51359	2	-	-	500	-	-	-	624	-	-
ECC weight	51359	2	-	-	90	-	-	-	100	-	-
Rider weight	51359	24	91.89	3.24	85.8	88.3	93.7	94.1	97.2	-0.38	-1.29
Extra weight	51359	12	41.19	41.78	0	0	49.5	58.8	107.6	0.4	-1.28
Total weight	51359	32	229.39	42.59	178.3	192.1	229.7	253.5	304.3	0.46	-1.17
Assistance level	51359	5	-	-	1	-	-	-	5	-	-

Variable	Ct.	Uq.	Mean	Std	Min	25%	Median	75%	Max	Sk	K
Speed	51359	1081	15.40	6.43	0	11.29	15.52	19.79	42.66	-0.03	0.2
Average slope	51359	98	0.18	1.73	-4.26	-0.84	0.23	1.23	4.59	-0.14	-0.23
Temperature	51359	27	3.96	6.13	-5	-1	2	7	21	0.83	-0.2
Voltage	51359	33847	46.10	5.09	35.54	40.28	47.99	50.45	53.66	-0.3	-1.56
Voltage rate	51359	590	0	0.01	-0.37	0	0	0	0.38	1.28	707.09
Current	51359	16006	-5.34	4.53	-18.9	-9	-4.16	-1.3	0	-0.59	-0.89
Current rate	51359	598	0	0.05	-1.85	-0.01	0	0.01	1.87	-0.07	807.21
Consumed amp-hours	51359	5316	-0.93	0.83	-4.10	-1.38	-0.71	-0.29	0	-1.27	1.70
Consumed amp-hours Rate	51359	45	0	0	0	0	0	0	0	2.14	7.97
SoC	51359	20190	89.12	13.88	38.03	81.7	96.51	99.56	100	-1.3	0.76
SoC rate	51359	45	0	0	-0.01	-0.01	0	0	0	-0.41	-1.44
Discharged energy	51359	42926	3.51	1.50	0.63	2.40	3.81	4.85	5.45	-0.47	-1.13
Discharged energy rate	51359	45	0	0	0	0	0	0	0	0.13	-1.25

The average *speed* measures 15.40 km/h, with skewness and kurtosis values suggesting relative symmetry.

The *average slope* measures 0.18% suggesting predominantly flat terrain. However, this variable has a standard deviation of 1.73% indicating variability with both descents and ascents ranging from -4.26% to 4.59%, respectively. The slight negative skewness arises from a minor predominance of downhill slopes.

An average *temperature* measures 3.96 °C due to data collection in cooler conditions, though the range from -5 to 21°C spans a wide temperature spectrum.

The electrical attributes, with an average *voltage* measuring 46.10 V and an average *current* measuring -5.34 A, reveal the electrical consumption patterns of the devices and battery discharge, as indicated by the negative current values. The skewness and kurtosis of voltage and current suggest slight deviations.

For battery usage, the mean *consumed amp-hours* and *state of charge (SoC)* are -0.93 Ah and 89.12%, respectively, implying a generally high SoC across the dataset. *Discharged energy* averages 3.51 kWh, with minimal mean change in the *discharged energy rate*.

The pronounced skewness and kurtosis in the *voltage rate* and *current rate* distributions indicate a sharper peak than a normal distribution as shown in Figure 19.

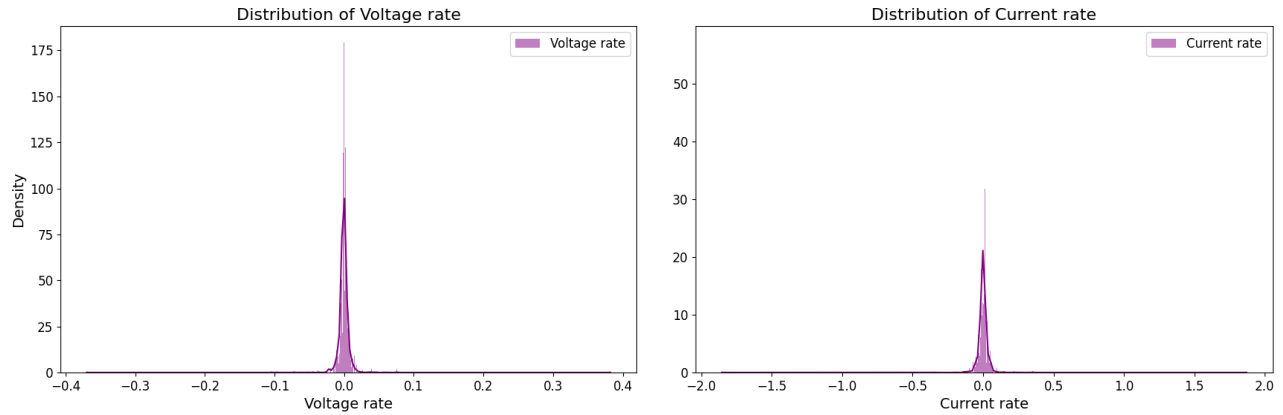


Figure 19: Distribution of Voltage Rate and Current Rate

The *average slope* distribution is shown in Figure 20, with multiple peaks, suggesting varying terrain or changes in the incline during the activities being monitored. Similarly, the *speed* distribution is multimodal due to varying traffic scenarios and riding habits.

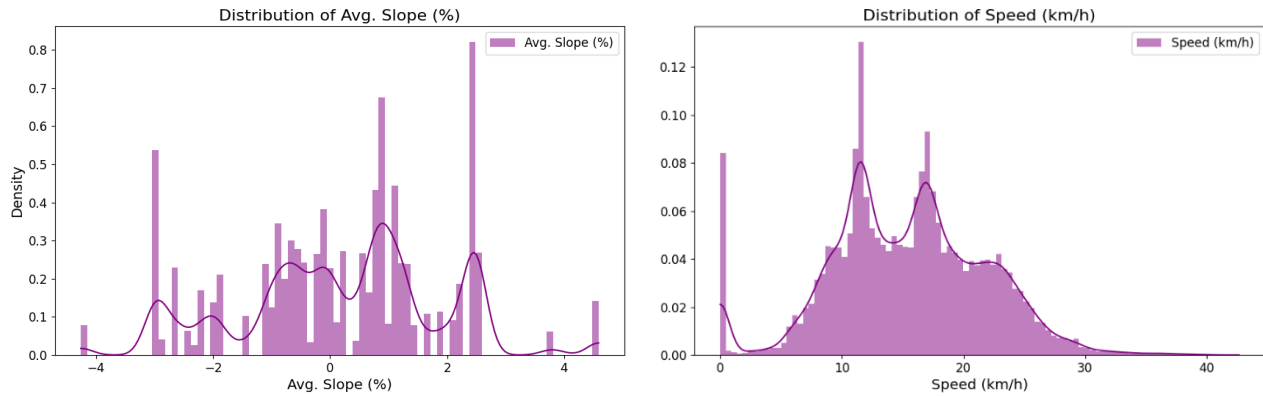


Figure 20: Distribution of Average Slope and Speed

Battery-related variables display unique behaviors as shown in Figure 21 and Figure 22. *Voltage* shows a bimodal distribution, indicative of two operational states, with Section 4.4 attributing this pattern to variations between ECCs. *Current* readings are mostly near zero amps, with spikes of increased activity peaking at approximately -12 amps. *Consumed amp-hours* is characterized by

a leftward skew, and the distribution of the *Consumed amp-hours rate* suggests significant variability, albeit with minor actual value changes.

The distribution of *discharged energy* exhibits a multimodal pattern, coming from its cumulative nature. Similarly, the *discharged energy rate* displays comparable multimodal characteristics but within a narrower range of 0 to 3×10^{-5} , suggesting a more uniform distribution than that of *discharged energy*. The *State of Charge (SoC)* is left-skewed, with a predominant frequency at 100%, indicating the common practice of beginning trips with a fully charged battery. The *SoC rate* predominantly clusters around zero, highlighting minimal variations in the SoC across most scenarios. As detailed in Section 4.4, these patterns are attributed to the low values associated with Babboe.

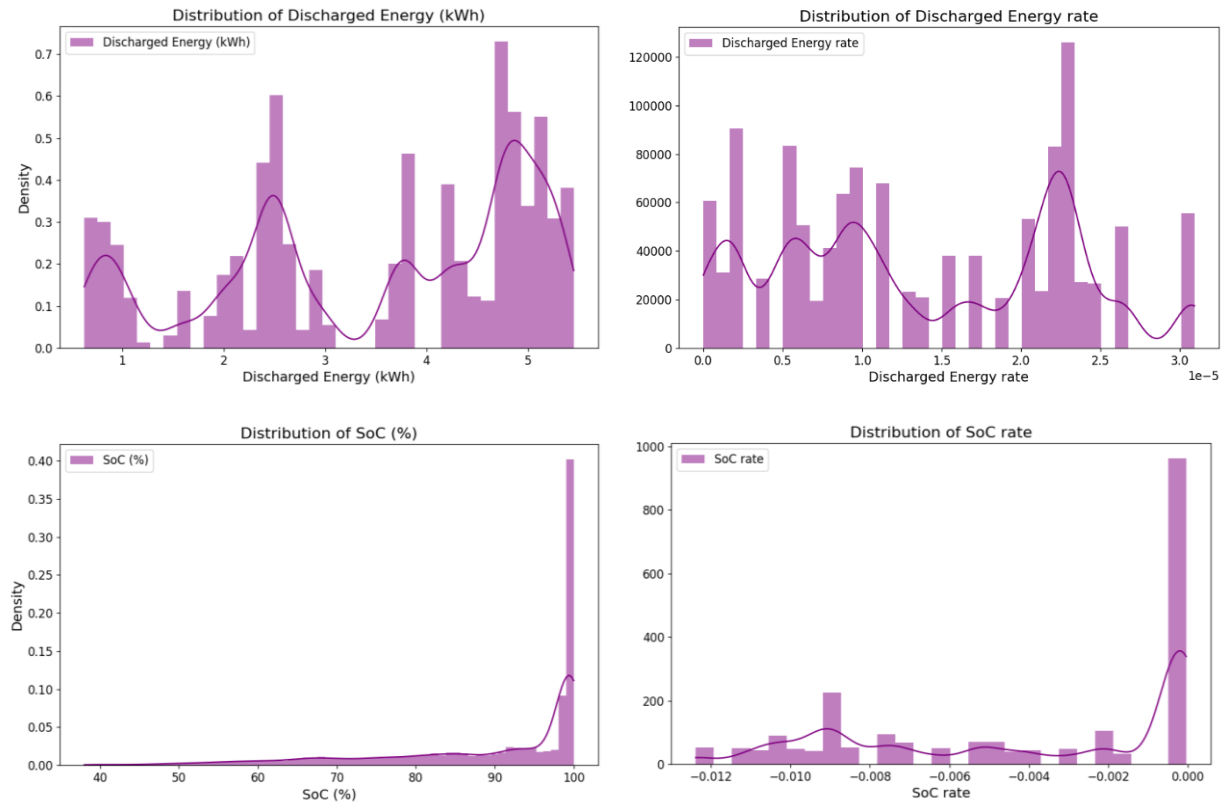


Figure 21: Distribution of Battery-Related Variables (1/2)

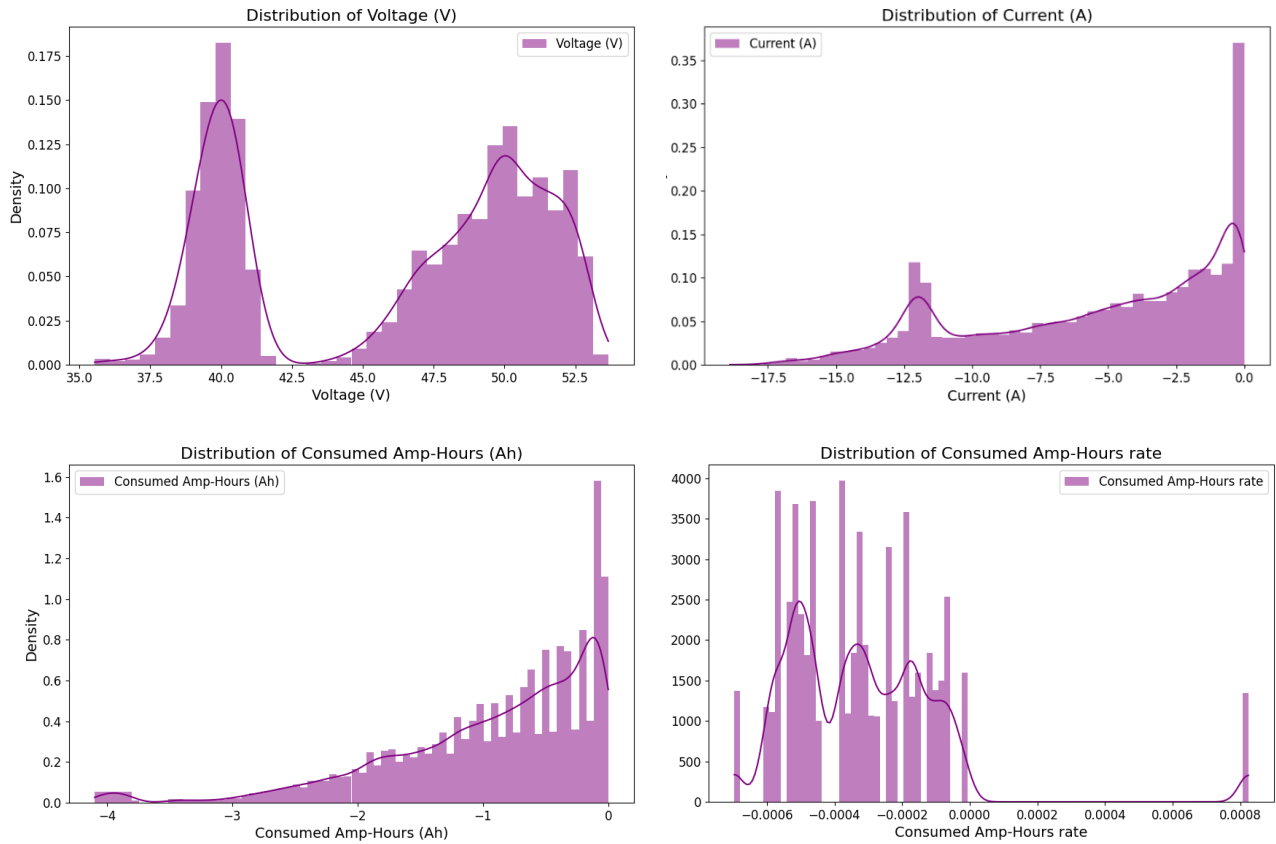


Figure 22: Distribution of Battery-Related Variables (2/2)

4.4. Summary Statistics by ECC

The summary statistics are presented in Table 15 with side-by-side comparisons for the two ECCs. Babboe exhibits a greater maximum *speed* up to 42.66 km/h, whereas Ami reaches a maximum of 34.20 km/h.

Ami demonstrates a broader *temperature* range, which is attributed to the larger range of dates for the data collection when compared to Babboe. In addition, Ami exhibits a higher *voltage*, likely due to its battery design.

In terms of energy usage, Ami shows higher consumption, as indicated by the higher values across battery-related variables such as *voltage*, *voltage rate*, *current*, *current rate*, *SoC*, *SoC rate*, *consumed amp-hours* and *consumed amp-hours rate*. However, Babboe shows a higher *discharged energy* due to the cumulative nature of this variable. Since Babboe was tested after Ami, it got the cumulative values from the battery monitor, beginning its measurement from Ami's final discharged energy value.

Table 15: Summary Statistics of the Final Dataset by ECC

Attribute	Ct.	Uq.	Mean	Std	Min	25%	Median	75%	Max	Sk	K
Date	32437 (18922)	16* (4)**	-	-	-	-	-	-	-	-	-
Time	32437 (18922)	21663 (179)	-	-	-	-	-	-	-	-	-
Model	32437 (18922)	1 (1)	-	-	-	-	-	-	-	-	-
Latitude	32437 (18922)	25317 (16152)	-	-	-	-	-	-	-	-	-
Longitude	32437 (18922)	27190 (16971)	-	-	-	-	-	-	-	-	-
Distance	32437 (18922)	30083 (18262)	2502.40 (2345.84)	1432.21 (1467.11)	0.00 (0.00)	1218.48 (1055.65)	2519.47 (2269.60)	3625.42 (3550.42)	5031.96 (5003.53)	0.00 (0.15)	-1.17 (-1.21)
Motor power	32437 (18922)	1 (1)	-	-	500.00 (250.00)	-	-	-	500.00 (250.00)	-	-
Torque	32437 (18922)	1 (1)	-	-	45.00 (70.00)	-	-	-	45.00 (70.00)	-	-
Battery Capacity	32437 (18922)	1 (1)	-	-	624.00 (500.00)	-	-	-	624.00 (500.00)	-	-
ECC Weight	32437 (18922)	1 (1)	-	-	100.00 (90.00)	-	-	-	100.00 (90.00)	-	-
Rider Weight	32437 (18922)	20 (6)	91.88 (91.91)	3.44 (2.85)	85.80 (88.30)	88.00 (88.30)	93.30 (94.00)	94.00 (94.50)	97.20 (95.00)	-0.38 (-0.35)	-1.22 (-1.80)
Extra Weight	32437 (18922)	9 (4)	42.41 (39.09)	41.74 (41.77)	0.00 (0.00)	0.00 (0.00)	56.80 (49.50)	58.80 (51.40)	107.10 (107.60)	0.31 (0.56)	-1.35 (-1.11)
Total Weight	32437 (18922)	21 (11)	234.29 (221.00)	42.48 (41.45)	185.80 (178.30)	193.30 (184.00)	243.90 (227.80)	253.50 (235.90)	304.30 (292.10)	0.40 (0.57)	-1.24 (-1.08)
Assistance Level	32437 (18922)	5 (4)	-	-	1.00 (1.00)	-	-	-	5.00 (4.00)	-	-
Speed	32437 (18922)	927 (1001)	14.67 (16.67)	6.20 (6.63)	0.00 (0.00)	11.15 (11.92)	14.68 (16.66)	18.37 (21.53)	34.20 (42.66)	-0.13 (0.03)	0.17 (0.13)
Average Slope	32437 (18922)	98 (98)	0.13 (0.28)	1.72 (1.73)	-4.26 (-4.26)	-0.92 (-0.78)	0.22 (0.50)	1.16 (1.31)	4.59 (4.59)	-0.13 (-0.17)	-0.28 (-0.14)

Attribute	Ct.	Uq.	Mean	Std	Min	25%	Median	75%	Max	Sk	K
Temperature	32437 (18922)	27 (19)	6.02 (0.43)	6.48 (3.19)	-5.00 (-4.00)	0.00 (-2.00)	6.00 (0.00)	11.00 (2.00)	21.00 (14.00)	0.40 (0.72)	-0.89 (0.11)
Voltage	32437 (18922)	22425 (11422)	49.76 (39.82)	2.02 (0.87)	43.34 (35.54)	48.37 (39.32)	49.96 (39.92)	51.36 (40.41)	53.66 (41.58)	-0.42 (-1.02)	-0.52 (2.34)
Voltage rate	32437 (18922)	367 (223)	0.00 (0.00)	0.01 (0.00)	-0.37 (-0.03)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.38 (0.01)	1.17 (-1.58)	507.43 (6.68)
Current	32437 (18922)	12406 (8008)	-6.17 (-3.92)	4.86 (3.47)	-17.40 (-18.90)	-11.21 (-5.78)	-5.45 (-2.80)	-1.33 (-1.29)	0.00 (0.00)	-0.27 (-1.16)	-1.29 (0.86)
Current rate	32437 (18922)	376 (222)	0.00 (0.00)	0.06 (0.02)	-1.85 (-0.13)	-0.01 (-0.01)	0.00 (0.00)	0.01 (0.01)	1.87 (0.06)	-0.05 (-0.76)	571.61 (3.02)
Consumed Amp-hours	32437 (18922)	4984 (1718)	-1.12 (-0.61)	0.93 (0.46)	-4.10 (-1.90)	-1.74 (-0.92)	-0.93 (-0.50)	-0.35 (-0.20)	0.00 (0.00)	-0.92 (-0.64)	0.53 (-0.52)
Consumed Amp-hours rate	32437 (18922)	27 (18)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	2.43 (0.19)	7.07 (-1.29)
SoC	32437 (18922)	19702 (1441)	83.04 (99.55)	14.30 (0.38)	38.03 (98.40)	73.22 (99.27)	86.02 (99.67)	95.06 (99.89)	100.00 (100.00)	-0.76 (-0.78)	-0.30 (-0.39)
SoC rate	32437 (18922)	27 (18)	-0.01 (0.00)	0.00 (0.00)	-0.01 (0.00)	-0.01 (0.00)	-0.01 (0.00)	0.00 (0.00)	0.00 (0.00)	0.38 (0.13)	-1.07 (-1.40)
Discharged Energy	32437 (18922)	26736 (1619)	2.63 (5.01)	1.21 (0.22)	0.63 (4.71)	1.91 (4.80)	2.52 (5.00)	3.80 (5.18)	4.70 (5.45)	-0.05 (0.29)	-1.09 (-1.26)
Discharged Energy rate	32437 (18922)	27 (18)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.69 (-0.15)	-0.73 (-1.07)

* Values for Ami

** Values for Babboe given in parenthesis

For the SoC variable, Ami experienced a reduction to 38%, while Babboe, owing to its battery technology, displayed a minimal discharge, showed a minimum SoC of 98%. This is a substantial difference when considering that both vehicles were operated for equal distances and in comparable conditions. Figure 23 illustrates these key variables and the distinctions between each ECC through box and whisker plots.

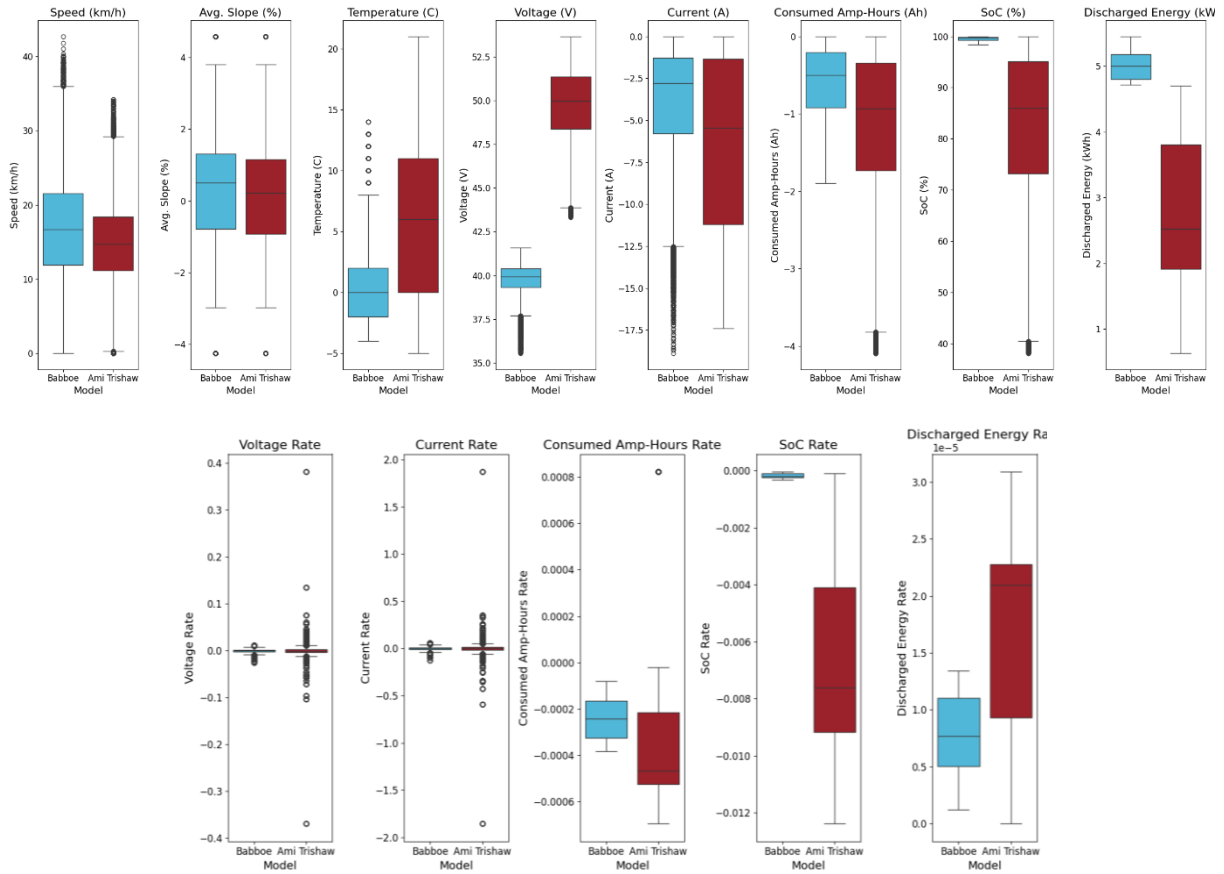


Figure 23: Box and Whisker Plots by Model

The detailed distribution of each variable also provides insights when compared by model, with the exception of the voltage rate and current rate, which present consistent distributions between models as shown previously in Figure 19.

The *average slope* distribution shown in Figure 24 does not indicate major deviations by ECC. In terms of *speed*, both vehicles exhibit multimodal distributions, yet Babboe tends to show smaller range of *speeds*, representing a more uniform pace. Ami, on the other hand, demonstrates a larger range, evidenced by its multiple peaks.

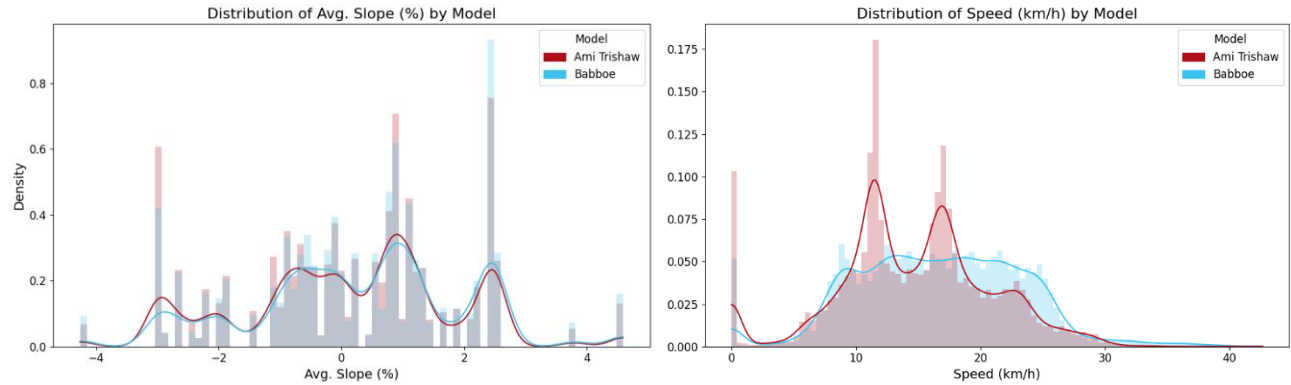


Figure 24: Distribution of Average Slope and Speed by ECC

Battery-related variables exhibit differences between ECCs as shown in Figure 25. The *voltage* for Babboe is not only lower on average, but also demonstrates a smaller range than Ami. The *current* distribution indicates that Ami exhibits higher current readings, suggesting a tendency for higher power usage. In contrast, Babboe exhibits lower *current* values with less variation, which points to a more consistent and more efficient energy usage pattern.

When examining *consumed amp-hours*, both models are left-skewed, yet Babboe has a longer tail towards lower energy consumption, while Ami shows a longer tail towards energy consumption. The variability in *consumed amp-hours rate* for Babboe exhibits fluctuations.

The *discharged energy* for Babboe is higher due to this variable's cumulative nature, when compared to Ami, but the *discharged energy rate* distribution is narrower, implying a tendency towards higher discharges.

The SoC distributions are closer to full capacity in Babboe when compared to Ami, and additionally show a smaller range for the *SoC rate*. This suggests that Babboe utilizes the battery more effectively during operation and lasts much longer.

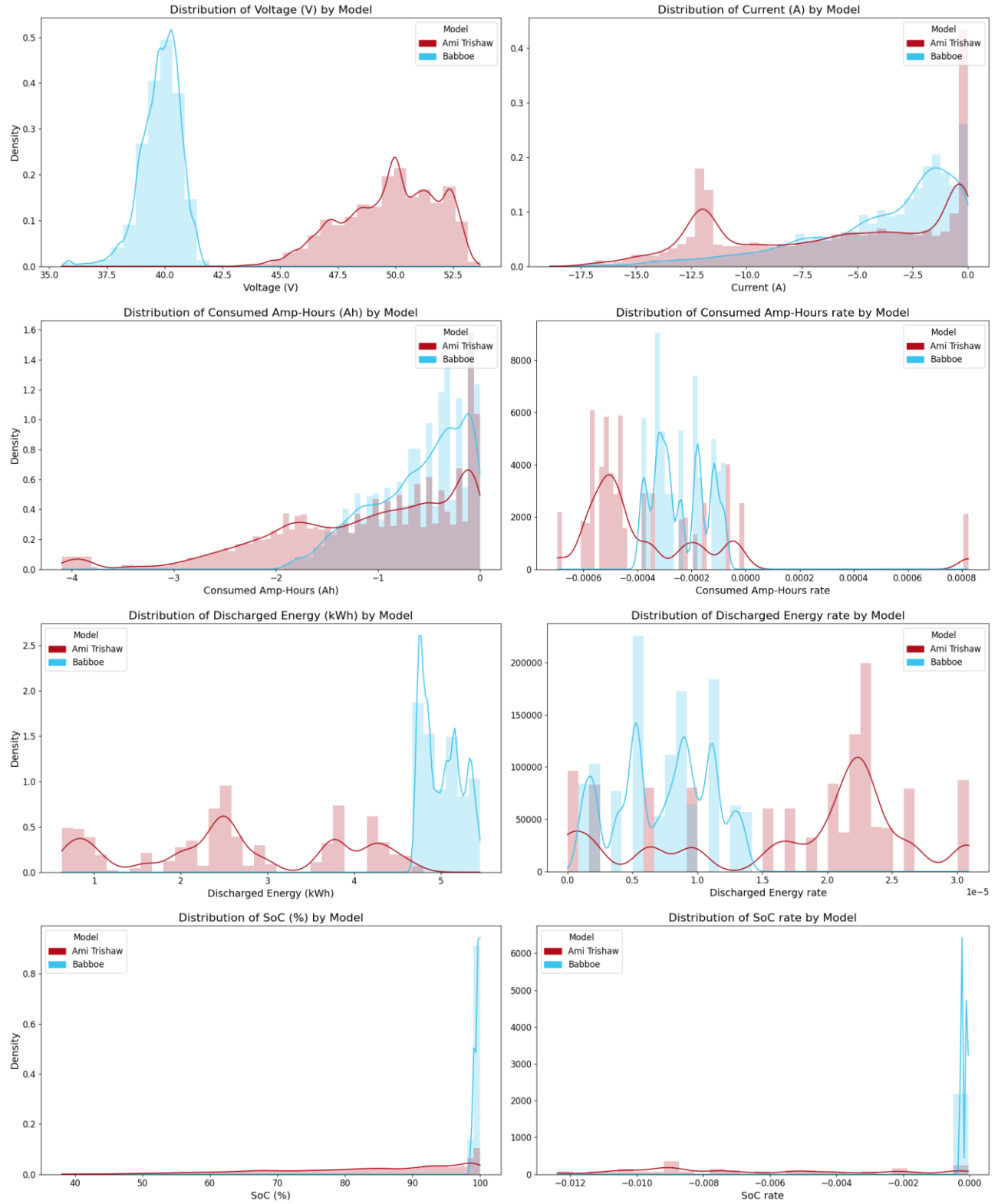


Figure 25: Distribution of Battery-Related Variables by ECC

Given the distinctly different behaviours identified for the two ECCs, a calibration of mathematical relationships tracking battery performance independently for each ECC yield more accurate predictions. Models combining the data for both ECCs are provided for comparative reference only.

4.1. Linear Correlations

Figure 26 shows the Pearson correlation coefficient matrix for the combined dataset in the first line, followed by Ami and Babboe. In addition, a p-value is given beside each Pearson value to indicate statistical importance.

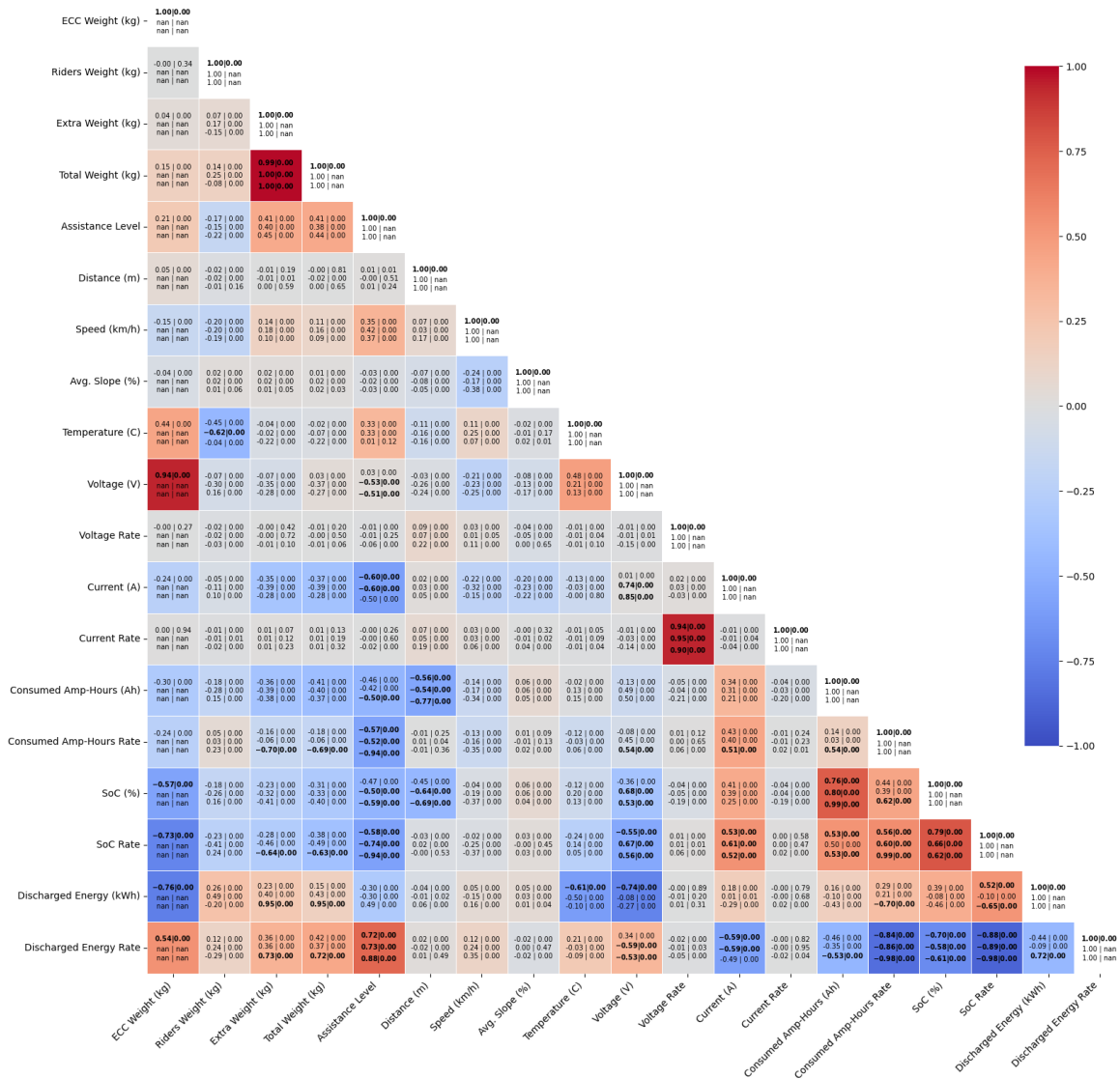


Figure 26: Pearson Correlation Coefficient Matrix

The *assistance level* exhibits a linear relationship to battery-related metrics across the combined dataset and each ECC, albeit with some exceptions like the consumed amp-hours and distance, with -0.56, -0.54 and -0.77 correlation for the combined dataset, Ami and Babboe, respectively, as shown in Figure 27. Babboe exhibits a moderate linear relationship between the battery-related variables and the *extra weight* and *total weight*, as shown in Figure 28.

Beyond the highlighted linear relationships in the matrix, scatterplots presented in Figure 29 visualize the non-linear nature of the data and the variability in behaviour across models. A Spearman correlation analysis is provided in the next section since this approach does not assume linearity.

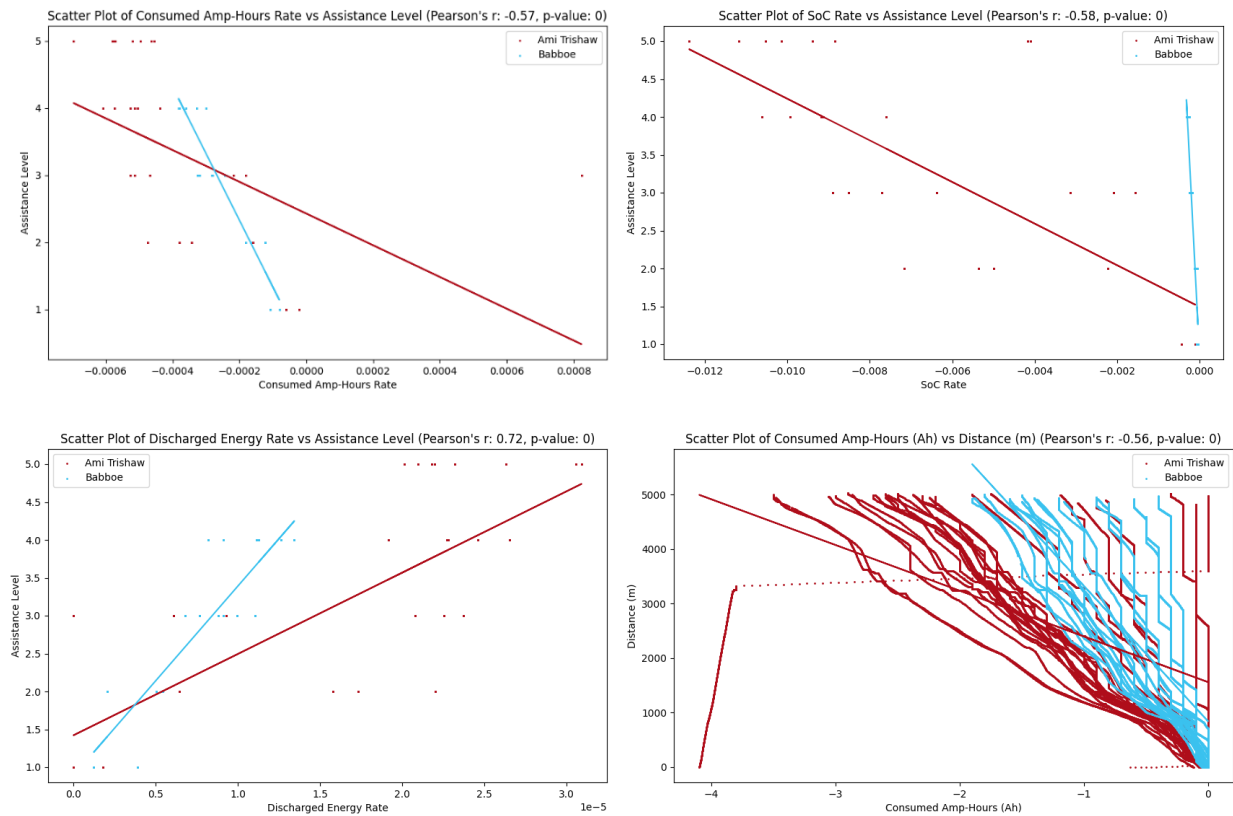


Figure 27: Variables with Moderate Linearity

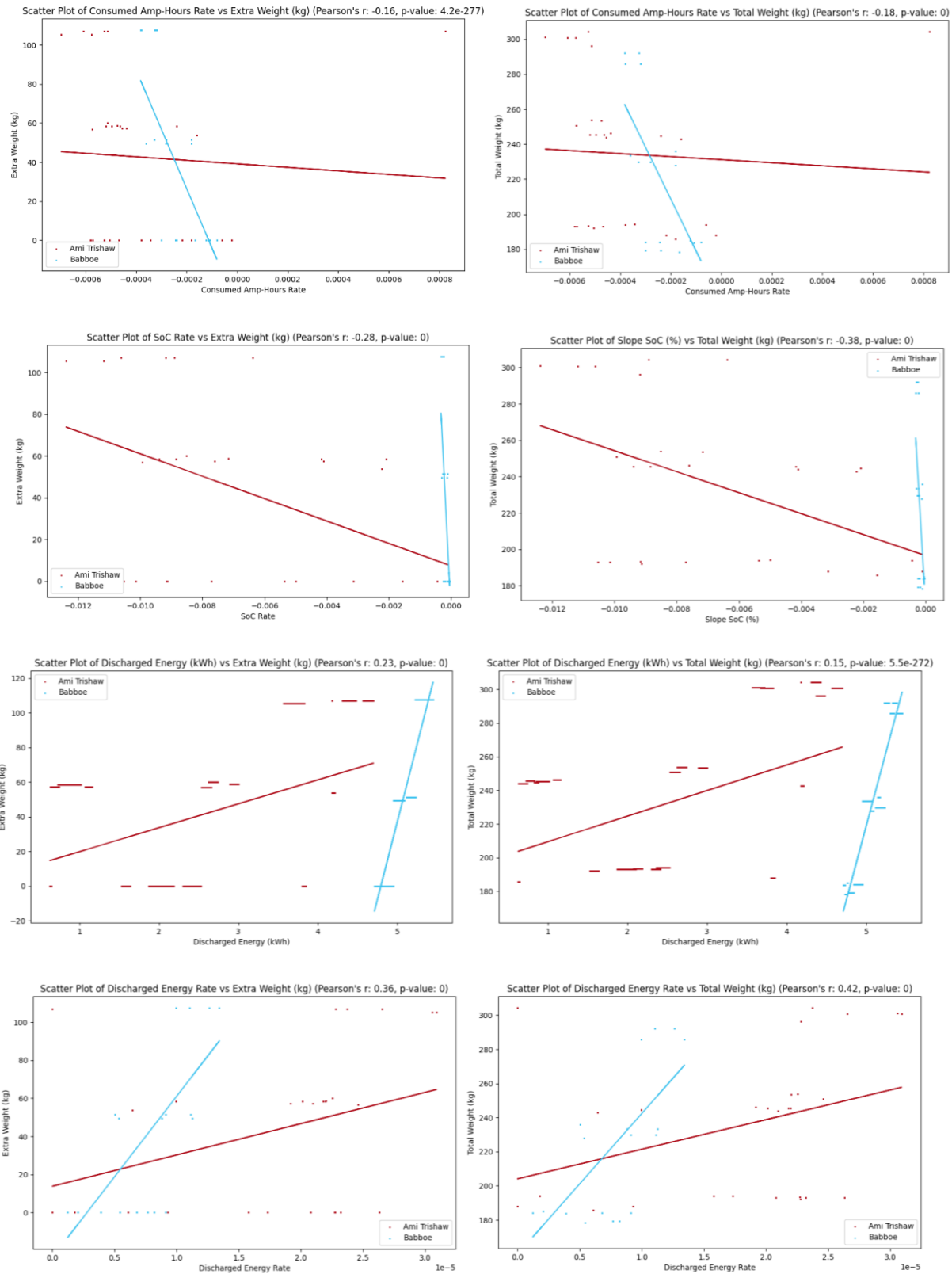


Figure 28: Variables with a Moderate Linearity for Babboe

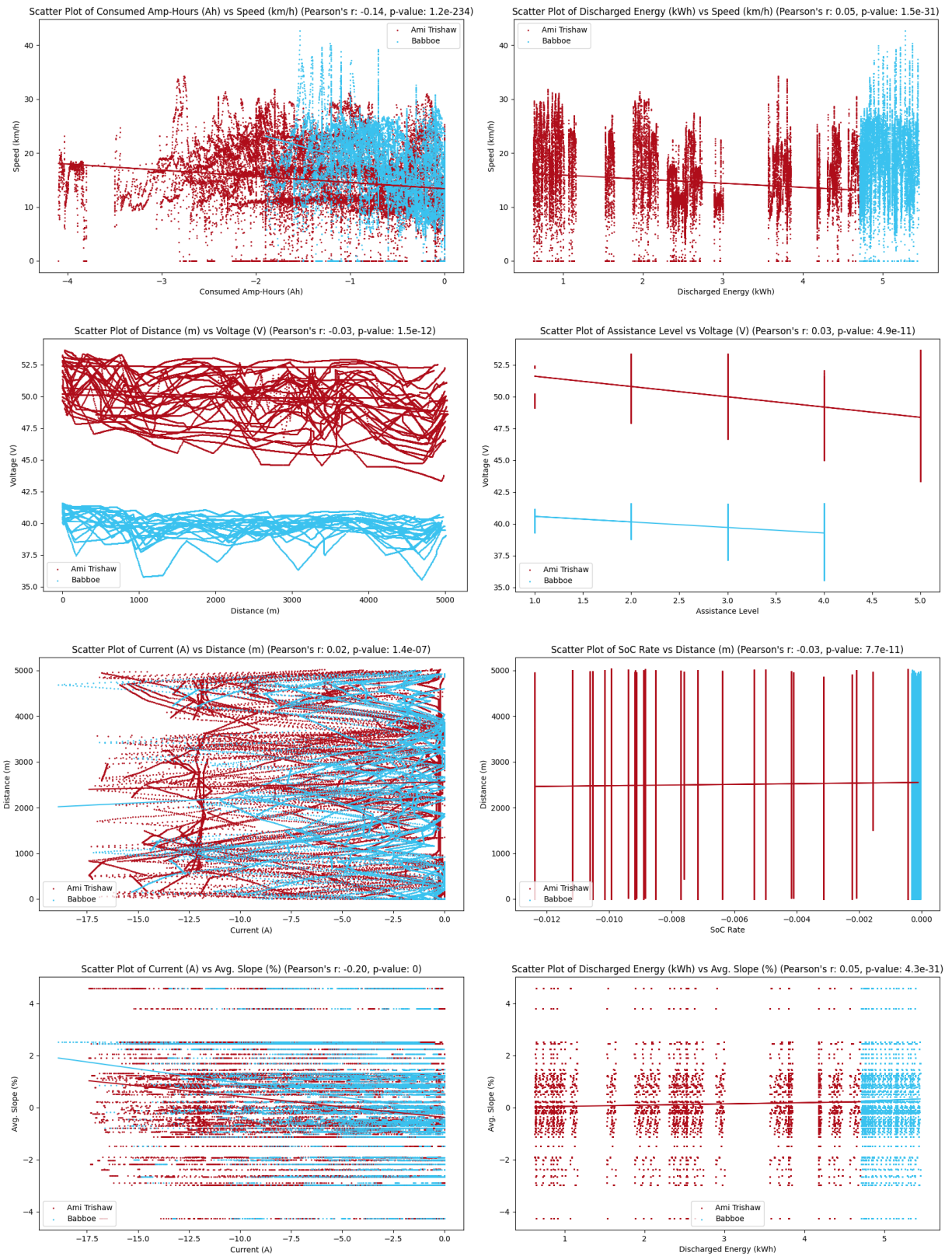


Figure 29: Variables with Low Linearity

4.2. Non-Linear Correlations

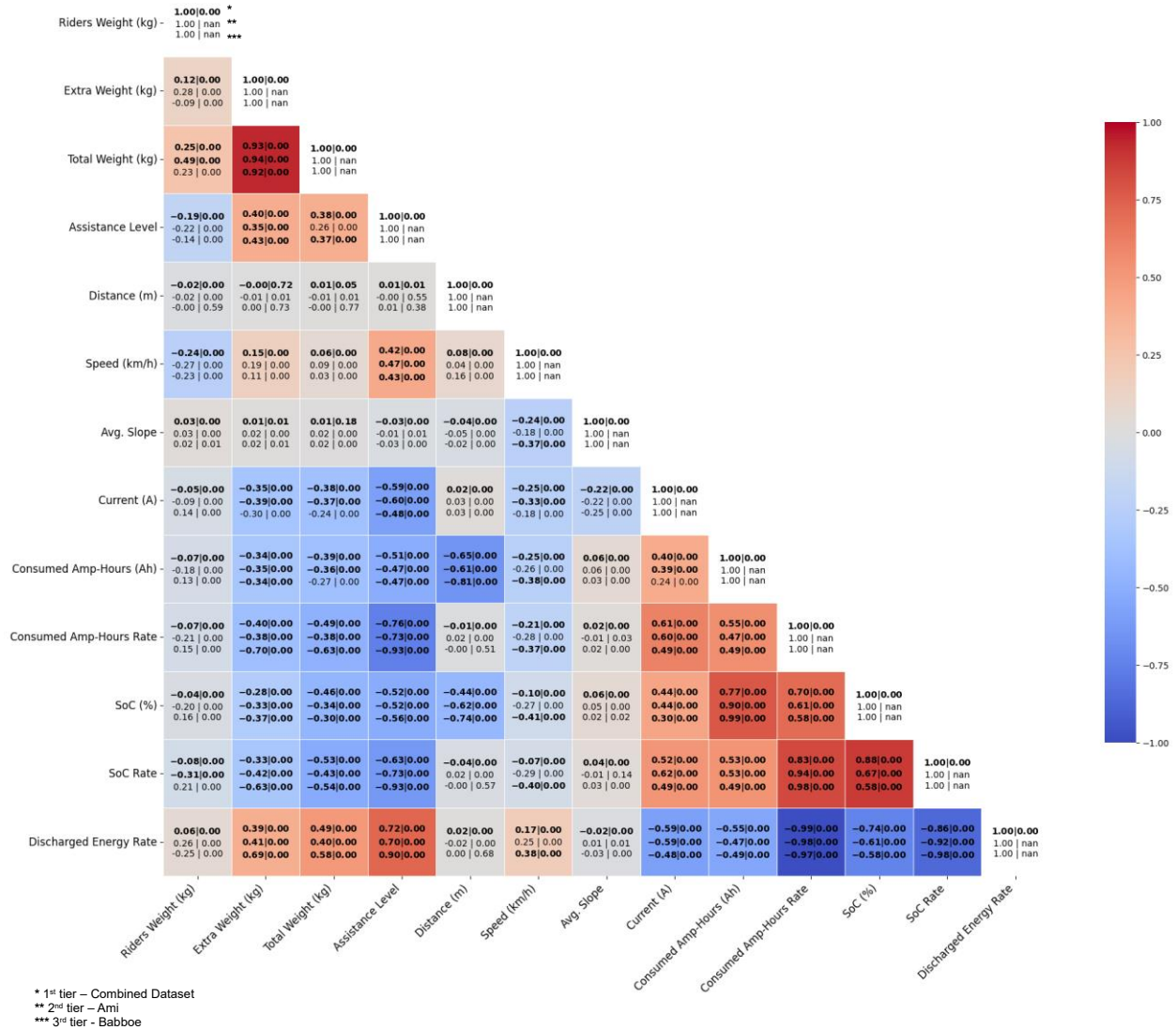


Figure 30: Spearman Correlation Matrix

Beyond the highlighted linear relationships in Figure 26, scatterplots presented in Figure 29, which include a line of best fit, clearly indicate the data's non-linear nature and the variability in behavior across models. Figure 30 shows the Spearman correlation matrix for the combined dataset and by ECC. *Total power, battery capacity, torque, ECC weight, temperature, voltage, voltage rate, current rate and discharged energy* won't be included in the analysis from now on due to the results in previous sections.

The analysis reveal that battery-related variables exhibit strong correlations with each other across the combined dataset and within individual models.

The correlation between *speed* and the *assistance level* is moderate across the dataset and for each ECC. However, Babboe exhibits a moderate correlation between *speed* and battery-related variables that does not persist for Ami. Contrary to popular understanding and established literature (Papaioannou et al., 2023; Hesselmanns, 2022; Fontaine, 2022; Arango et al., 2021; Rudolph & Gruber, 2017; Nocerino et al., 2016; Duin et al., 2013), the *average slope* appears not to be a significant factor in variables like *SoC* and *consumed amp-hours*, questioning the commonly held view of its strong link with battery consumption. Despite the intuitive expectation that riding uphill demands more power than riding on flat ground, the motor does not exceed its maximum output and reduces the speed. As a result, *consumed amp-hours* also decreases, showing a more pronounced correlation than that between voltage and slope as shown in Figure 31.

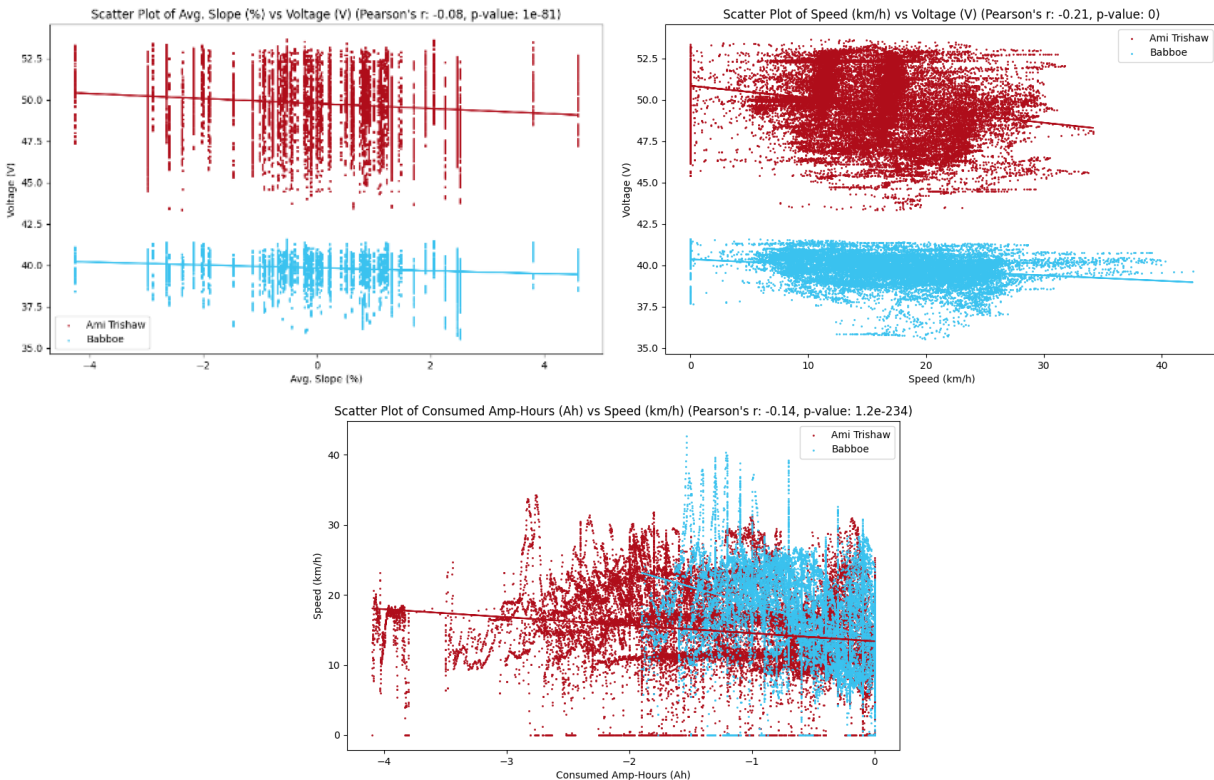


Figure 31: Average Slope, Speed, Voltage and Consumed Amp-hours Relationships

Variables including *extra weight*, *total weight*, *assistance level*, and *distance* appear to be key in explaining battery usage across the dataset and among the two ECCs based on Figure 30. *Extra weight* shows the strongest correlation with the *consumed amp-hours rate*, followed by the *discharged energy rate* across the dataset and among the two ECCs. Distance exhibits

a significant correlation with *consumed amp-hours* for the combined dataset and yet shows a stronger correlation with SoC for the individual Babboe and Ami models.

When focusing on the separate models for Babboe and Ami, the *SoC rate* becomes more prominent.

For the combined dataset and Ami, the *total weight* correlates strongly with the *SoC rate*. For Babboe, the *total weight* is more strongly correlated to the *consumed amp-hours rate*. The *assistance level* is notably correlated with the *consumed amp-hours rate* across the two ECCs and the combined dataset, followed by the *discharged energy rate*.

Given these findings, modelling strategies that do not rely on the assumption of linearity and normality are preferable. This includes polynomial regression and machine learning techniques such as neural network or random forest, which are more adept at capturing the complex relationships within the data.

4.3. Chapter Summary

This chapter delves into the intricate dynamics of ECC performance, employing a thorough examination of raw data, outlier analysis, and both linear and non-linear statistical methods to unravel the nuanced interactions between operational parameters and battery efficiency. The insights not only provide a foundational understanding of ECC behaviour under varying conditions but also underscore the necessity for sophisticated analytical approaches to predict performance and optimize electric cargo cycling experiences.

An initial section explored the raw data with simple observations, revealing insights into the behaviour of the two electric cargo cycles (ECCs), Ami and Babboe, under different conditions. Key observations included both ECCs demonstrating a direct relationship between assistance levels and speed, with Ami showing a notably steeper decline in State of Charge (SoC) at higher assistance levels. Additional weight negatively affected speed and SoC for both models, with Babboe exhibiting a broader speed range and a more significant SoC decline under heavier loads. The analysis highlighted Babboe's superior performance in terms of speed and energy efficiency.

Outlier identification focused on variables such as speed, slope, and temperature. The analysis led to the exclusion of data points with extreme temperature and slope values, based on discrepancies with official records and the inherent characteristics of the dataset. The remaining dataset, post-cleaning, consisted of 51,359 data points, deemed more representative for further analysis.

The combined dataset laid the foundation for an in-depth statistical analysis, unveiling an average speed of 15.40 km/h across terrain that was predominantly flat, as indicated by an average slope of 0.18%. The analysis also uncovered bimodal distributions in various variables, reflecting the distinct behaviours exhibited by the two ECCs.

A comparison of the Ami and the Babboe datasets highlighted differences in maximum speeds, with Babboe achieving higher velocities; variability in energy consumption patterns, with Ami showing higher values across several battery-related variables; and Babboe exhibiting a more efficient battery usage, maintaining higher SoC levels under comparable conditions.

Analysis of linear and non-linear correlations reaffirmed the complex relationships between speed, assistance level, and battery metrics, as well as the non-linear nature of the datasets. Spearman correlation analysis revealed strong correlations among battery-related variables and identified key factors influencing battery usage, such as extra weight and total weight. The analysis recommended advanced modelling techniques beyond linear assumptions to accurately capture the dataset's dynamics.

5. The Electric Cargo Cycle Battery (ECCB) Model

This chapter builds upon the data analysis laid out in previous sections, where *extra weight*, *total weight*, *assistance level*, and *distance* were identified as significant factors influencing battery performance. Through testing and comparison of different statistical and machine learning models, including Polynomial Regression (PR), Random Forest (RF) and Neural Network (NN), the chapter aims to identify the most accurate and reliable methods for predicting battery performance in real-world ECC scenarios.

Moreover, the chapter delves into accuracy validation and sensitivity analysis, providing insights into the model's reliability and its response to changes in key variables. These analyses offer a deeper understanding of how different operational conditions and configurations can impact the state of charge (SoC) and, by extension, the overall effectiveness of ECCs in urban logistics.

5.1. Model Selection

Variables including *extra weight*, *total weight*, *assistance level*, and *distance* hold substantial correlations on battery performance as shown in Chapter 4. These variables subsequently provide linkages to ECC deployment and routing. The battery performance can be directly tracked as a dependent variable using *consumed amp-hours*, *consumed amp-hours rate*, *SoC*, *SoC rate* and *discharged energy rate*, but ended up selecting the dependent variable that has the highest prediction results.

Table 16 outlines various modelling scenarios for evaluating these decision variables against target variable through the different datasets.

Table 16: Modelling Scenarios for the Battery Model

Modelling Scenario	Dependent Variable	Independent Variables
1	consumed amp-hours (Ah)	extra weight (kg), total weight (kg), assistance level, distance (m)
2	consumed amp-hours rate (Ah/m)	extra weight (kg), total weight (kg), assistance level
3	SoC (%)	extra weight (kg), total weight (kg), assistance level, distance (m)
4	SoC rate (%/m)	extra weight (kg), total weight (kg), assistance level
5	discharged energy rate (kWh/m)	extra weight (kg), total weight (kg), assistance level

Table 17 presents the comparative results and metric values for the various models, encapsulating both the comprehensive dataset and the different ECCs.

Table 17: Modelling Scenarios Results

Model	Model Parameters	Dataset	RMSE	MAE	R ²
Modelling scenario 1 (x,y)* = ((extra weight, total weight, assistance level, distance), consumed amp-hours)					
PR	2**	Combined	0.41	0.21	0.755
PR	3**		0.37	0.17	0.804
PR	4**		0.36	0.18	0.817
RF	200, 10 ***		0.33	0.10	0.840
NN	3, 100 ****		0.30	0.10	0.868
PR	2	Ami	0.50	0.26	0.711
PR	3		0.43	0.19	0.793
PR	4		0.40	0.15	0.816
RF	200, 10		0.41	0.12	0.811
NN	3, 100		0.38	0.14	0.829
PR	2	Babboe	0.06	0.05	0.983
PR	3		0.05	0.04	0.990
PR	4		0.04	0.03	0.994
RF	300, None		2.01E-03	1.00E-03	1.000
NN	3, 100		0.03	0.02	0.996
Modelling scenario 2 (x,y) = ((extra weight, total weight, assistance level), consumed amp-hours rate)					
PR	2	Combined	1.85E-04	9.48E-05	0.473
PR	3		1.61E-04	7.78E-05	0.599
PR	4		1.49E-04	4.11E-05	0.659
RF	300, 10		1.48E-04	3.30E-05	0.662
NN	3, 100		1.87E-04	1.12E-04	0.457
PR	2	Ami	2.03E-04	1.05E-04	0.538
PR	3		1.83E-04	6.60E-05	0.624
PR	4		1.81E-04	4.93E-05	0.633
RF	200, 10		1.81E-04	4.93E-05	0.634
NN	3, 200		2.46E-04	1.85E-04	0.321
PR	2	Babboe	8.21E-06	7.08E-06	0.993
PR	3		1.08E-11	9.78E-12	1.000
PR	4		6.04E-14	5.92E-14	1.000
RF	200, 5		1.71E-18	1.44E-18	1.000
NN	3, 200		4.90E-05	4.00E-05	0.742
Modelling scenario 3 (x,y) = ((extra weight, total weight, assistance level, distance), SoC)					
PR	2	Combined	4.34	3.18	0.902
PR	3		3.13	2.21	0.949
PR	4		2.75	1.82	0.961
RF	300, 10		1.01	0.41	0.995
NN	3, 100		2.04	0.98	0.978
PR	2	Ami	3.59	2.66	0.937
PR	3		2.79	1.81	0.962
PR	4		1.73	1.13	0.986

Model	Model Parameters	Dataset	RMSE	MAE	R ²
RF	300, 10	Babboe	1.15	0.51	0.994
NN	3, 100		2.35	1.16	0.972
PR	2		0.06	0.04	0.979
PR	3		0.04	0.03	0.990
PR	4		0.03	0.03	0.993
RF	300, None		1.69E-03	8.08E-04	1.000
NN	3, 200		0.09	0.08	0.944

Modelling scenario 4 (x,y) = ((extra weight, total weight, assistance level), SoC rate)

PR	2	Combined	1.41E-03	1.11E-03	0.887
PR	3		9.46E-04	6.97E-04	0.949
PR	4		6.64E-04	3.28E-04	0.975
RF	300, 10		2.84E-04	7.94E-05	0.995
NN	3, 100		8.55E-04	5.19E-04	0.958
PR	2	Ami	1.13E-03	8.72E-04	0.899
PR	3		8.75E-04	5.19E-04	0.940
PR	4		3.47E-04	1.18E-04	0.990
RF	200, 10		3.47E-04	1.18E-04	0.990
NN	3, 100		9.08E-04	5.63E-04	0.935
PR	2	Babboe	9.52E-06	7.79E-06	0.989
PR	3		1.36E-11	1.23E-11	1.000
PR	4		5.14E-14	5.07E-14	1.000
RF	200, 5		9.39E-19	7.83E-19	1.000
NN	3, 300		5.22E-05	3.36E-05	0.669

Modelling scenario 5 (x,y) = ((extra weight, total weight, assistance level), discharged energy rate)

PR	2	Combined	4.11E-06	2.84E-06	0.793
PR	3		3.26E-06	2.07E-06	0.869
PR	4		2.69E-06	1.04E-06	0.911
RF	300, 10		2.62E-06	6.40E-07	0.916
NN	-		-	-	-
PR	2	Ami	4.25E-06	2.83E-06	0.783
PR	3		3.24E-06	1.25E-06	0.875
PR	4		3.20E-06	9.57E-07	0.877
RF	200, 10		3.20E-06	9.57E-07	0.877
NN	-		-	-	-
PR	2	Babboe	6.57E-07	5.61E-07	0.967
PR	3		3.24E-14	2.70E-14	1.000
PR	4		6.47E-15	6.33E-15	1.000
RF	100, 10		4.32E-20	3.74E-20	1.000
NN	-		-	-	-

* x = independent variables, y = dependent variable

** Degree for PR

*** Number of trees, depth level for RF

**** Number of hidden layers, neurons per hidden layer for NN

	Optimal Outcome
	Moderate Performance
	Least Favorable Result

For the Random Forest (RF) model, a range of tree counts (10, 50, 100, 200, 300), and depth levels (5, 10, 20) are tested to fine-tune the model performance. A similar approach is employed for the Neural Network (NN) model, where various configurations of hidden layers (1, 2, 3) and number of neurons (50, 100, 200, 300) are evaluated to determine the most effective architecture.

The least effective models across the various analyses are those based on NN and Polynomial Regression (PR) model with a degree of 2. For the modelling scenario 5, the NN model presented negative R^2 , meaning that the model does not follow the trend of the data, despite the multiple configurations and functions tested. This outcome suggest that the model performance was inferior even to a simplistic approach of using a horizontal line to represent the mean of the dependent variable and was overfitting. In contrast, the most successful models are found to be the PR model using a degree of 4 and the RF model.

The Babboe dataset models provided the best overall goodness of fit indicating more predictability when compared with Ami. The best modelling scenarios include Scenario 3, with the SoC as the dependent variable, and Scenario 4, with the SoC rate as the dependent variable.

Figure 32 and Figure 33 evaluate the residuals versus predicted values for the PR and the RF models for scenarios 3 and 4. For both the PR and the RF models, the Scenario 4 (*SoC rate*) residuals are evenly distributed around zero for all datasets. The RF model outperforms the PR model in both modelling scenarios, leading to its selection for further examination of the residual pattern, as shown in Figure 34.

When comparing residual patterns across scenarios 3 and 4, the Scenario 4 (*SoC rate*) performs better across all datasets. As a result of the residuals and performance metrics, the RF model for the modelling scenario 4 (*SoC rate*), is selected for the Electric Cargo Cycle Battery (ECCB) model with the characteristics of tree counts and maximum depth shown in Table 18.

Table 18: ECCB Random Forest Model Results

Dataset	Trees	Max Depth	RMSE	MAE	R²
Combined	300	10	0.00	7.936E-05	0.995
Ami	200	10	3.47E-04	1.18E-04	0.990
Babboe	200	5	5.138E-14	5.068E-14	1.000

The Electric Cargo Cycle Battery (ECCB) model with SoC rate as dependent variable and extra weight, total weight, and assistance level as the independent variables.

Table 19 outlines the variable importance of the ECCB model across different datasets. For the combined dataset, the *total weight* emerges as a significant predictor, showing the highest correlation with the *SoC rate* compared to the other variables. In contrast, the *assistance level* is the key variable for the Ami and Babboe datasets, particularly for Babboe, where it accounts for 91% of the predictive value. Meanwhile, *extra weight* ranks as the least significant value for Babboe yet holds moderate importance for both the combined and Ami datasets.

Table 19: Variable Importance

Independent Variable	Combined	Ami	Babboe
Extra weight	0.20	0.23	0.02
Total weight	0.59	0.22	0.07
Assistance level	0.21	0.56	0.91

Figure 35 and Figure 36 illustrate individual trees from the ECCB model, specifically Tree 2 for Ami and Tree 11 for Babboe, respectively. While these individual trees can be interpreted on their own, the collective ensemble, or forest, created by the model doesn't lend itself to straightforward interpretation as mentioned in Section 3.7.1. Therefore, only two trees are presented to provide insight into their structural composition.

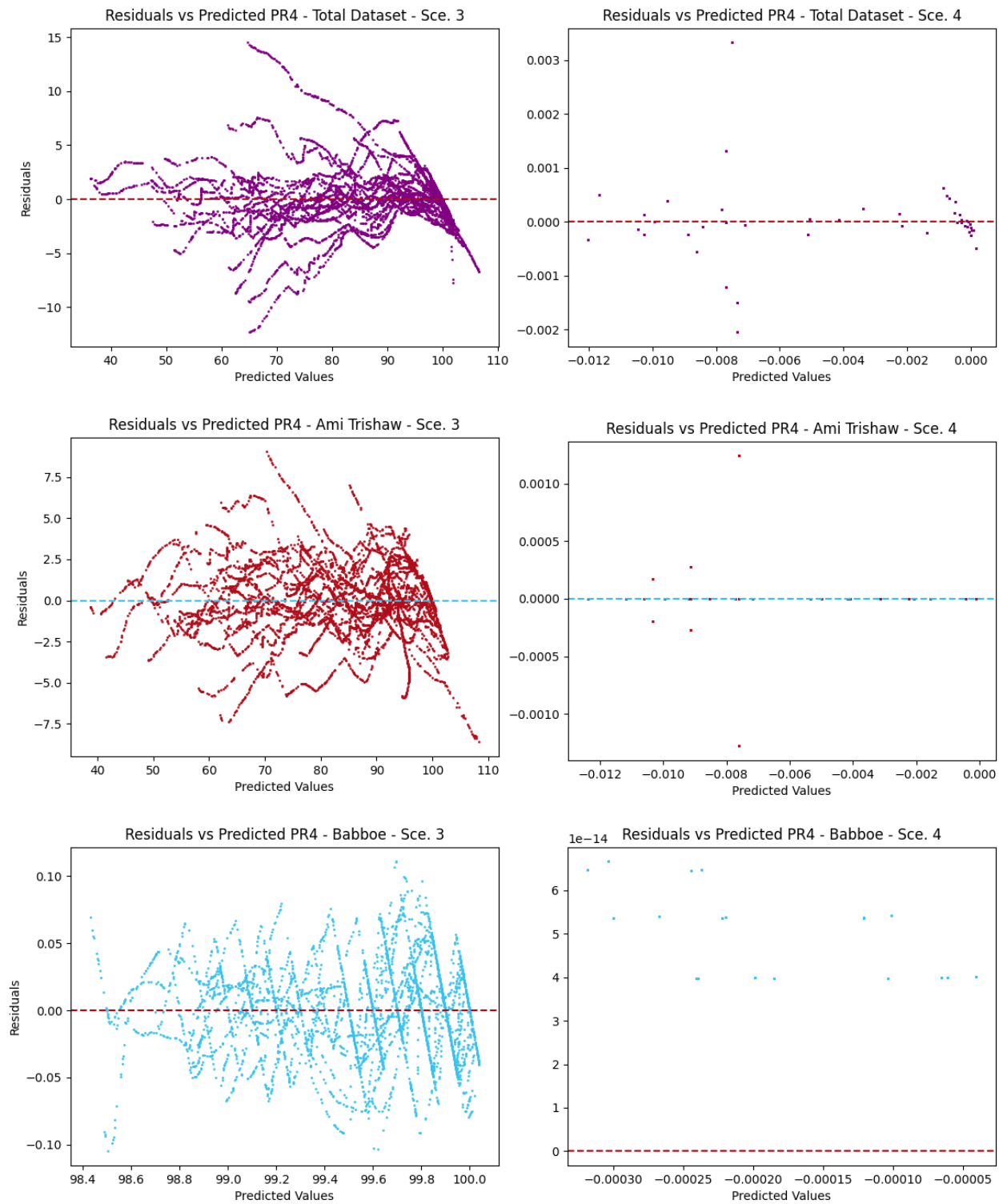


Figure 32: Polynomial (4th Degree) Regression Residuals for Scenario 3 and Scenario 4

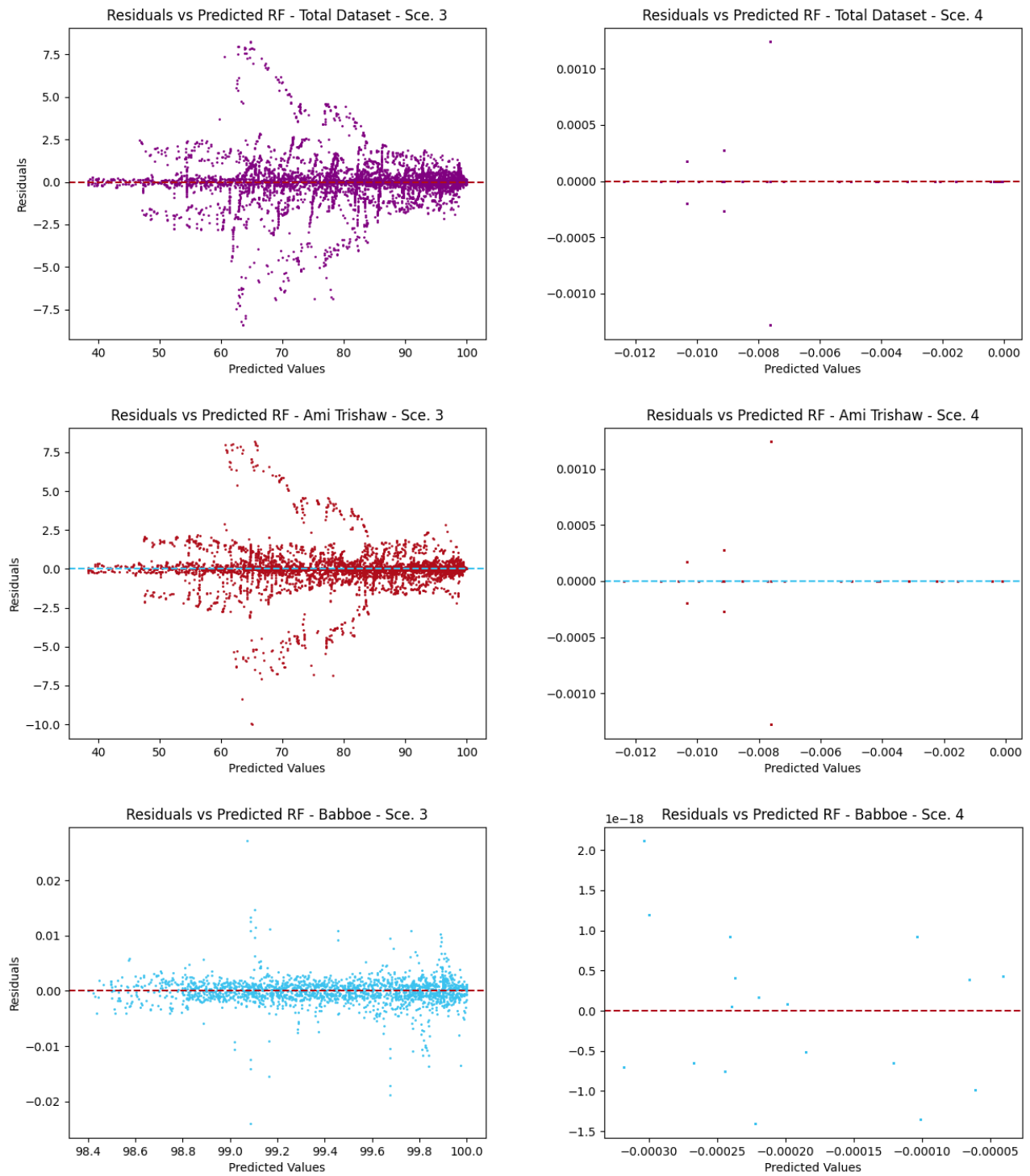


Figure 33: Random Forest Residuals and Predicted Values for Scenario 3 and Scenario 4

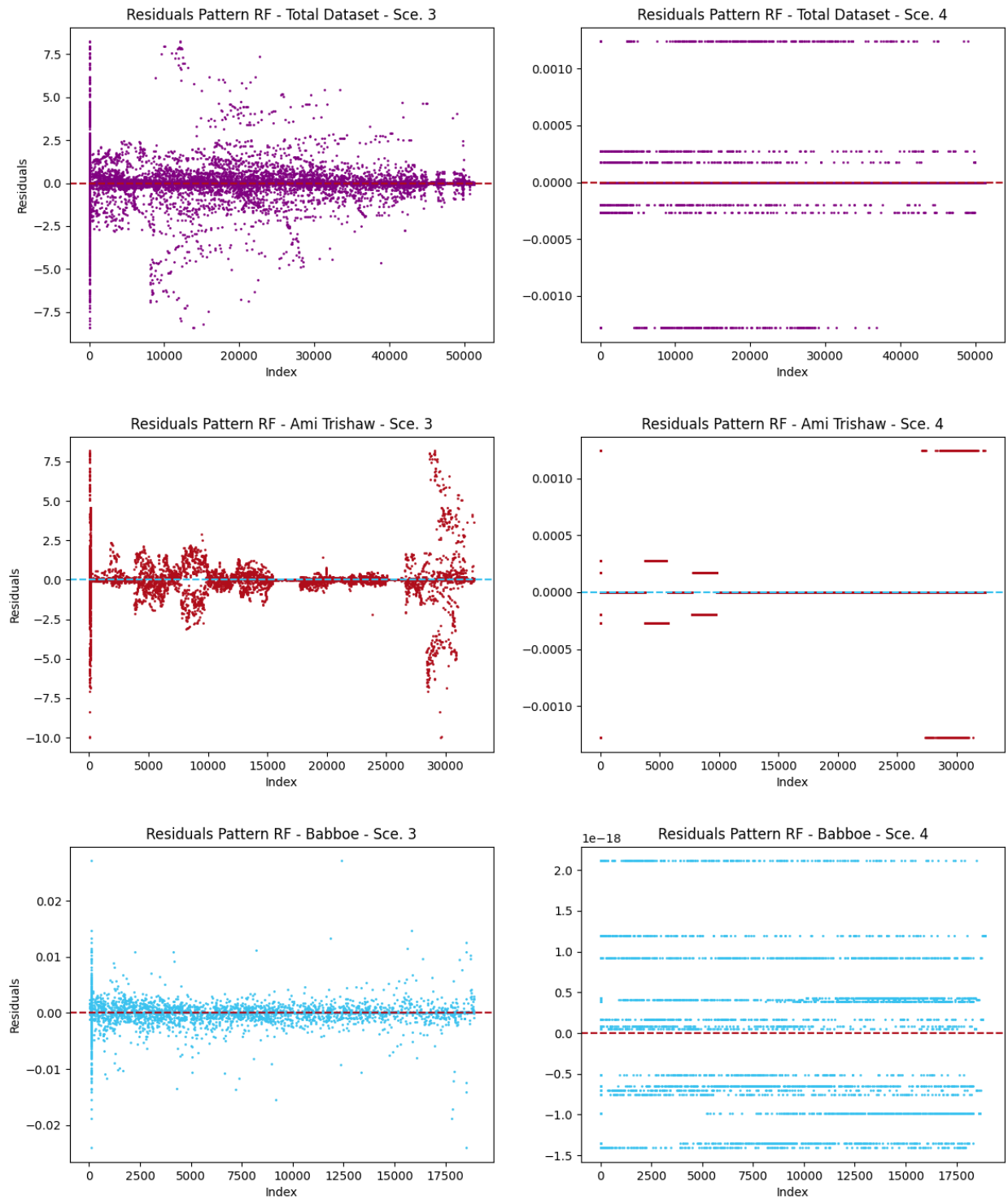


Figure 34: Random Forest Model Residuals by Index for Scenario 3 and Scenario 4

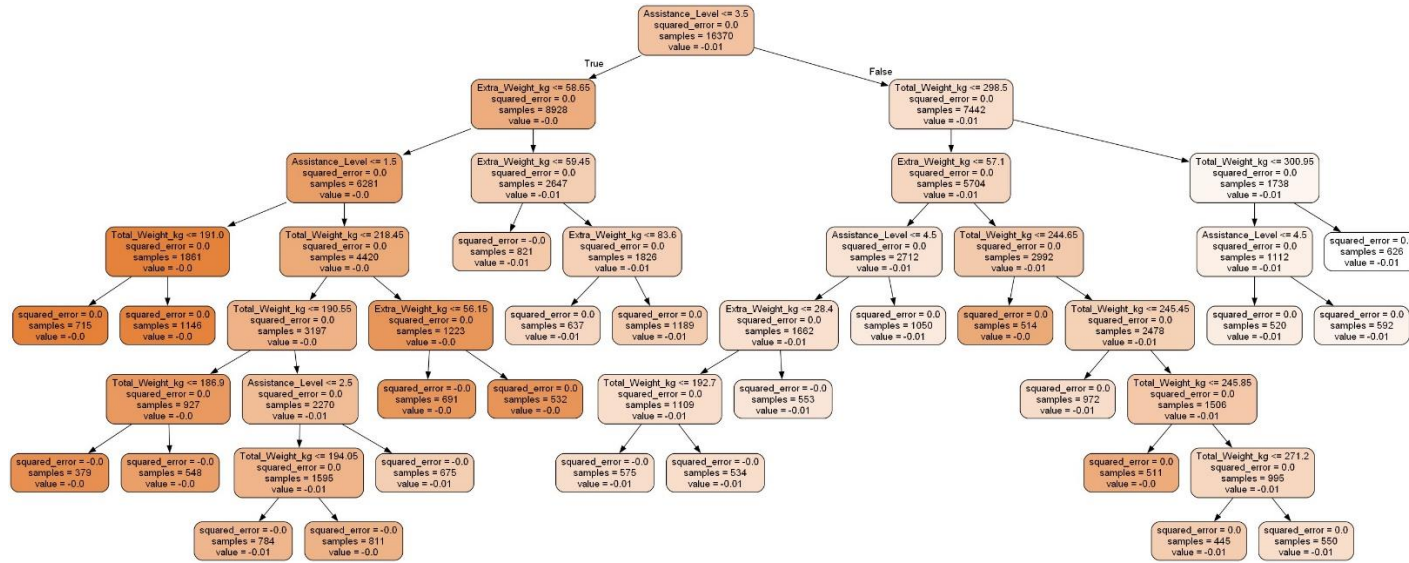


Figure 35: Example Tree from the ECCB model - Ami

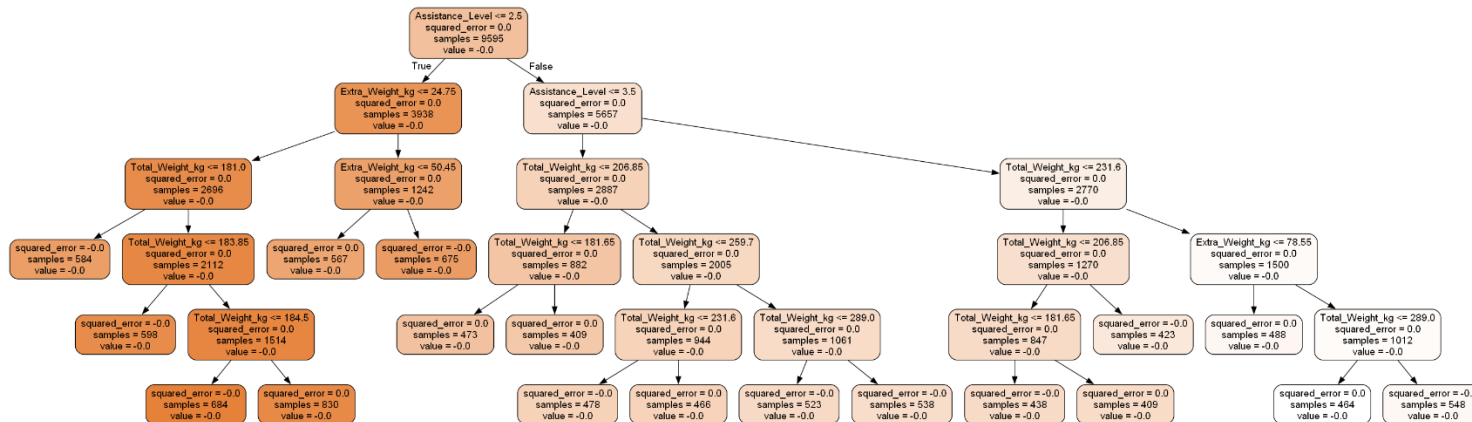


Figure 36: Example Tree from the ECCB model - Babboe

5.2. Model Validation

Table 20 presents a comparison between the predicted SoC data and the actual SoC data used to build the ECCB model. The methodology to calculate the results is given in section 3.7.3.

Table 20: Model Validation Using the Data Collection Scenarios for Predicted Versus Observed Data

Data collection Scenario *	Ami***			Babboe****			Combined*****		
	Real	Predicted	Error	Real	Predicted	Error	Predicted	Error Ami	Error Babboe
W0L1**	98.65	97.80	0.86%	99.75	99.67	0.08%	99.48	-0.84%	0.27%
W0L2	73.84	73.23	0.83%	99.60	99.67	-0.07%	99.48	-34.72%	0.12%
W0L3	72.86	61.48	15.62%	99.06	99.08	-0.02%	92.17	-26.50%	6.96%
W0L4	53.91	54.37	-0.85%	98.80	98.80	0.00%	92.17	-70.97%	6.71%
W0L5	47.26	48.36	-2.33%	-	-	-	48.50	-2.62%	-
W50L1	-	-	-	-	-	-	-	-	-
W50L2	76.31	85.16	-11.60%	99.45	99.44	0.01%	88.83	-16.41%	10.68%
W50L3	73.28	89.56	-22.22%	98.91	98.89	0.02%	89.10	-21.59%	9.92%
W50L4	55.68	50.31	9.64%	98.60	98.50	0.10%	89.10	-60.02%	9.63%
W50L5	66.03	48.36	26.76%	-	-	-	79.50	-20.40%	-
W100L1	-	-	-	-	-	-	-	-	-
W100L2	-	-	-	-	-	-	-	-	-
W100L3	61.46	61.86	-0.65%	98.80	98.81	-0.01%	98.78	-60.72%	0.02%
W100L4	50.20	54.11	-7.79%	98.45	98.41	0.04%	98.48	-96.18%	-0.03%
W100L5	38.16	58.62	-53.62%	-	-	-	79.23	-107.63%	-
Avg.	-	-	-3.78%	-	-	0.02%	-	-43.22%	4.92%

* W represents extra weight and L the assistance level

** Distance of 5 km for all scenarios for predicted values

*** Ami used 0, 56.95 and 106.25 kg for the different extra weights and 191.50 kg to include rider weight and ECC weight for predicted values

**** Babboe used 0, 50.45 and 107.60 kg for the different extra weights and 181.50 kg to include rider weight and ECC weight for predicted values

***** Combined used 0, 53.70 and 106.93 kg for the different extra weights and 186.50 kg to include rider weight and ECC weight for predicted values

For Ami, the real values fluctuate significantly across scenarios, from a high of 98.65 in W0L1 to a low of 38.16 in W100L5. Predictions are generally close to the real values, with some notable exceptions, such as W0L3, W50L2, W50L3, W50L5 and W100L5, where the prediction error is substantial.

For Babboe, the real values are consistently high, from 98.41 to 99.67. Predicted values are very close to real values, with negligible error percentages, and an average error of 0.02%, indicating high accuracy in the predictions for this ECC.

For the combined dataset, the predicted values show a higher variance when compared to Ami and Babboe. The error rates for Ami are negative in all scenarios, meaning the predictions consistently underestimated. On the other hand, errors for Babboe swing from positive to negative

but remain relatively small, except for W50L2, W50L3 and W50L4. The average errors are -43.22% for Ami and 4.92% for Babboe within the combined dataset. This suggests that the model used for the combined predictions may be less suited for Ami and more suited for Babboe. The high error rates in the combined dataset indicate that combining the data from both ECCs is not the best approach for predictive modelling.

Based on the above testing, the ECCB model will only apply using the separate models for the Ami and Babboe datasets.

When comparing the testing predicted data with the observed dataset in Figure 37, there is consistency across the Ami and the Babboe datasets in terms of the spread and distribution of points relative to the dashed line that suggests that the ECCB model is robust and generalizes well as depicted with an R^2 of 0.99 for Ami and 1.00 for Babboe.

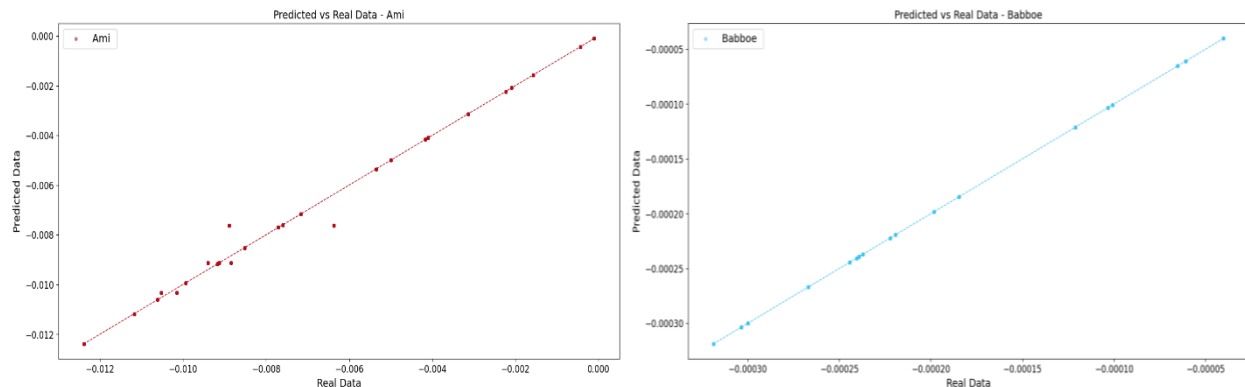


Figure 37: ECCB model SoC rate Prediction Versus SoC rate Observed Data

5.3. Sensitivity Analysis

Figure 38 shows the sensitivity analysis performed with the Ami and the Babboe datasets using the ECCB model.

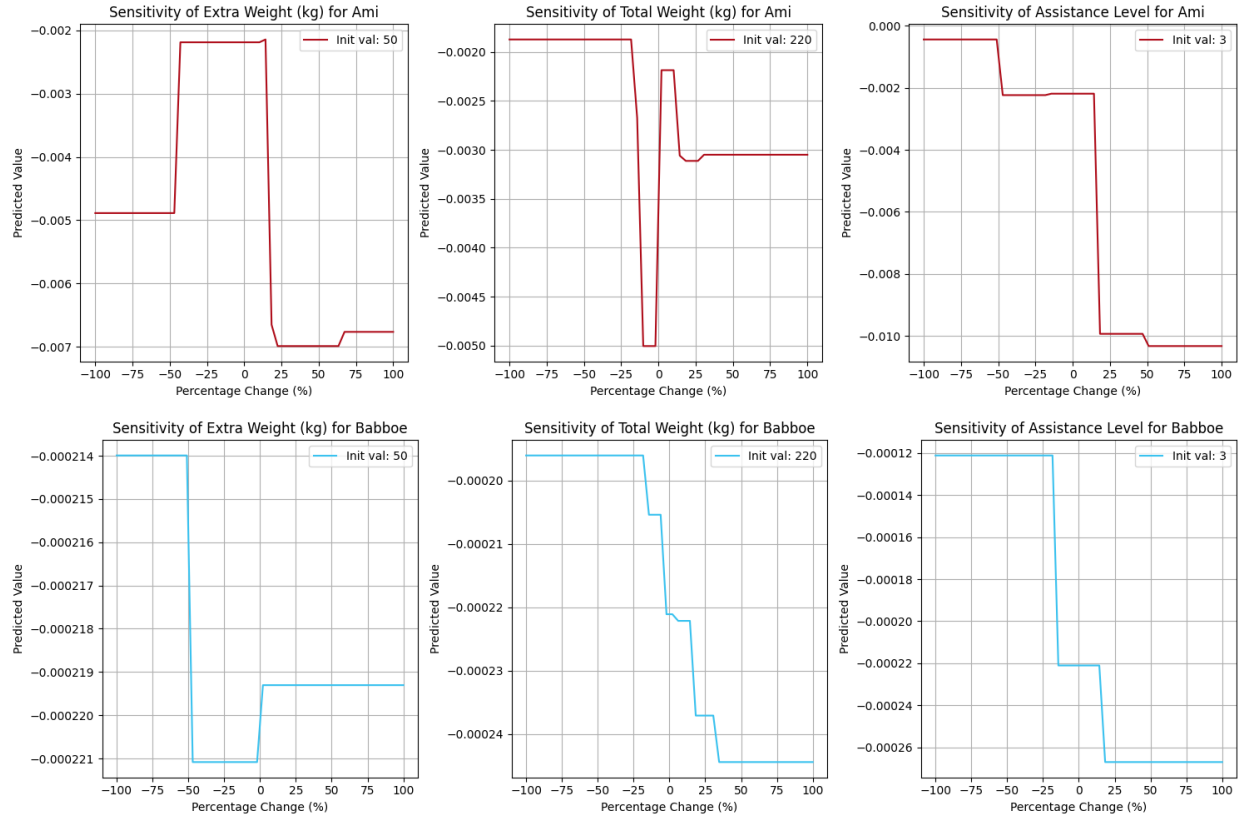


Figure 38: Sensitivity Analysis

For Ami, the *SoC rate* decreases sharply as the *extra weight* increases from the initial value, reaching a plateau around a 25% increase (62.5 kg). There's a significant drop in the *SoC rate* when the *extra weight* is reduced by 25% (37.5 kg) from the initial value. The *SoC rate* plateaus again beyond a 50% reduction (25 kg) in *extra weight*. Furthermore, the *SoC rate* decreases as the *total weight* is reduced by about 25% (165 kg), then slightly increases with further reduction before dropping again. With an increase in *total weight*, there is a slight drop in the *SoC rate* around the 25% increase mark (275 kg), after which the value stabilizes even with further increases. Additionally, the *SoC rate* declines steeply as the *assistance level* is reduced, suggesting that the model is sensitive to decreases in this variable as confirmed by Table 19. When the *assistance level* is increased, the *SoC rate* drops after a 25% increase (4) and then plateaus beyond a 50% increase (5).

For Ami, the most significant changes in the *SoC rate* occur with changes between -25% and 25% around the baseline values of the independent variables, indicating that the ECCB model is most sensitive to changes within this range.

For Babboe, the *SoC rate* slightly decreases with an increase in *extra weight*, notably around a 25% increase. There's a minor drop in *SoC rate* with a decrease in *extra weight*. Conversely, the *SoC rate* shows a notable decrease when the *total weight* decreases, with significant steps down around 25% and 50% reductions. There is little change in the *SoC rate* for increases in *total weight*, indicating that the model is not as sensitive to weight gain compared to weight loss for Babboe. When the *assistance level* drops, the *SoC rate* significantly decreases, with sharp decreases at 25% and 50% reductions, which translate in *assistance levels* of 2 and 1, respectively. Similar to Ami, the *SoC rate* changes little with increases in *assistance level*.

The significant changes in the *SoC rate* for Babboe occur within the range of -50% to +25% of the initial values of the independent variables. The sensitivity for *extra weight* for Babboe shows less volatility compared to Ami, suggesting that the ECCB model is less sensitive to changes in *extra weight* as confirmed by Table 19.

5.4. Chapter Summary

This chapter establishes the ECCB model as a pivotal tool for understanding and optimizing electric cargo cycle battery performance, underscored by thorough model testing, validation, and sensitivity analyses.

This section examines the variables impacting battery performance in electric cargo cycles (ECC), namely extra weight, total weight, assistance level, and distance. These variables are crucial for ECC deployment and routing decisions, with battery performance measured through metrics like consumed amp-hours and state of charge (SoC).

Various models are tested, including Polynomial Regression (PR), Random Forest (RF) and Neural Network (NN), with adjustments in degree, tree counts, depth levels, hidden layers, and neuron counts to optimize performance. Findings indicated that PR of degree 4 and RF models are the most effective, whereas NN and PR with a degree of 2 models, performed the worst.

The Babboe dataset models had the highest predictability, particularly in scenarios involving SoC and SoC rate as dependent variables. RF models excelled in these scenarios, demonstrating the best residual distributions and R^2 results. The RF models are selected for the ECCB battery prediction model.

Variable importance analysis revealed total weight as a significant predictor for the combined dataset, while assistance level was more critical for Ami and Babboe datasets, with extra weight being the least significant for Babboe.

Comparisons between predicted and actual data highlighted fluctuating real values for the Ami dataset across various scenarios, with the ECCB model tending to slightly underestimate these values. For Babboe, predictions are highly accurate, indicating the model's efficacy for this dataset. However, combining Ami and Babboe datasets led to larger prediction errors, suggesting that separate models for each dataset are preferable.

Sensitivity analysis for the Ami and Babboe datasets using the ECCB model showed distinct reactions to changes in extra weight, total weight, and assistance level. The Ami dataset is particularly sensitive to changes within a -25% to +25% range, while the Babboe dataset exhibited significant SoC rate decreases with reductions in weight and assistance level, indicating different sensitivities to variable changes between the two datasets.

6. The Electric Cargo Cycle Routing Problem (ECCRP) Model

6.1. The Base ECCRP Model

The Electric Cargo Cycle Routing Problem (ECCRP) evolves from the Capacitated Vehicle Routing Problem (CVRP), a staple in logistics and transportation optimization focused on finding the optimal route for delivering goods using vehicles with a specified capacity limit. In the context of ECCs, the challenge incorporates the battery capacity as a critical factor.

The case study assumes a logistics company operates several ECCs to serve delivery or pickup points from a single depot. Each ECC must start its route from the depot with a full battery, visit customers without creating sub-tours, make only one round-trip per day, and return to the depot without exceeding the carrying capacity or depleting its battery beyond the battery range. However, the latter constraint is later modified to allow multiple batteries to be used. while never exceeding the load capacity of the ECC and making sure it does not run out of power before returning to the depot. Each ECC must depart from the depot, carrying all assigned deliveries, and then return with the items collected during its route. An example of this routing is shown in Figure 39 for four ECCs.

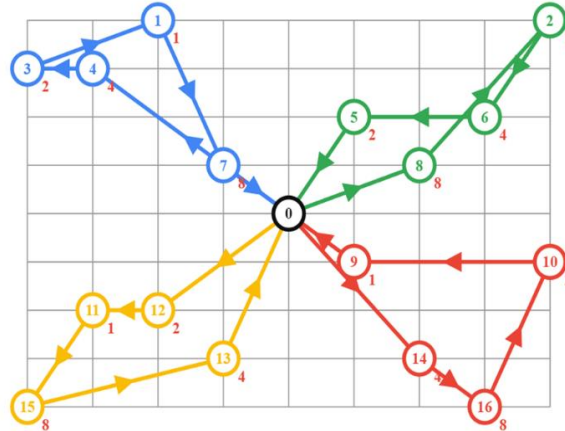


*Figure 39: Vehicle Routing Problem
(Google OR-Tools, 2023)*

The elimination of subtours ensures that each ECC route starts at the depot, serves a subset of customers, and returns to the depot without creating smaller loops that don't link back to the depot until all assigned customers are served.

The objective is to satisfy all customer demands at the lowest possible cost, under the constraints that each ECC has a single round trip from the depot per day, without considering specific delivery

times or penalties for delays. Key parameters for ECCs are shown in Table 12, such as motor power (P_t), battery capacity (Q), battery range (L_{max}), maximum speed (v_{max}), and load capacity (LC), are predefined by the ECC. It is assumed that the motors and batteries are not modified beyond the original manufacturer's specifications. The issue with determining battery capacity, as shown in *Eq. (13)*, lies in its dependency on motor power, which does not remain constant. Although V_{max} is subject to variation, not always being on the maximum value, accurately determining the value of P_T is challenging. Consequently, rather than relying on battery capacity as a gauge, L_{max} will serve as the benchmark that should not be surpassed.

$$Q = \frac{L_{max} P_T}{v_{max}} \quad \text{Eq. (13)}$$

To formulate the ECCRP, the logistics company must ensure its fleet of ECCs (K) can cover all customer locations ($i, j \in n$) without going over the battery range or exceeding load capacity, aiming for the minimum travel cost. The depot is represented for i and j as "0".

The formulation of the problem is articulated through *Eq. (14)* to *Eq. (24)*. The main goal, as outlined in *Eq. (14)* is to minimize the overall distance covered from i to j , denoted by c_{ij} . A series of constraints are applied to ensure operational efficiency and feasibility. *Eq. (15)* ensures that the vehicle (k) does not exceed its carrying capacity (LC_k) at any point in the route, *Eq. (16)* mandates that each pickup must be paired with a delivery for the same vehicle, and *Eq. (17)* ensures that a pickup at location i is followed by a delivery at location j . *Eq. (18)* requires that each location i , except the depot (0), sends out one vehicle. *Eq. (19)* is concerned with adhering to the maximum battery range ($L_{max,k}$) of each vehicle. To avoid incomplete routing solutions, *Eq. (20)* is dedicated to preventing subtours not involving the depot, using auxiliary variables representing the position in the tour (u_i, u_j). *Eq. (21)* ensures that the pickup location i is visited before the delivery location j . *Eq. (22)* and *Eq. (23)* allows each vehicle to start and end at the depot. *Eq. (24)* introduces a binary variable (x_{ijk}) to indicate whether an ECC is assigned to a particular customer.

$$\text{Min} \sum_{k=1}^K \sum_{j=0, j \neq i}^n \sum_{j=0, j \neq i}^n c_{ij} x_{ijk} \quad \text{Eq. (14)}$$

s.t.

$$\sum_{j=0}^n q_i x_{ijk} \leq LC_k, \quad \forall i \neq 0, \forall k \in K \quad \text{Eq. (15)}$$

$$\sum_{j=0}^n x_{ijk} = \sum_{j=0}^n x_{jik}, \quad \forall i \neq 0, \forall k \in K \quad \text{Eq. (16)}$$

$$x_{ijk} = 1 \rightarrow x_{jik} = 0, \quad \forall i \neq j, \forall k \in K \quad \text{Eq. (17)}$$

$$\sum_{k=1}^K \sum_{i=0,}^n x_{ijk} = 1 \quad \forall i, j \neq 0 \quad \text{Eq. (18)}$$

$$\sum_{i=0}^n \sum_{j=0, j \neq i}^n c_{ij} x_{ijk} \leq L_{max,k} \quad \forall k \in K \quad \text{Eq. (19)}$$

$$u_i - u_j + n x_{ijk} \leq n - 1, \quad \forall i, j \neq 0, \forall k \in K \quad \text{Eq. (20)}$$

$$u_i < u_j, \quad \text{if } x_{ijk} = 1, \quad \forall i, j \neq 0, \forall k \in K \quad \text{Eq. (21)}$$

$$\sum_{j=1}^n x_{0jk} = 1, \quad \forall k \in K \quad \text{Eq. (22)}$$

$$\sum_{i=1}^n x_{i0k} = 1, \quad \forall k \in K \quad \text{Eq. (23)}$$

$$x_{ijk} \in \{0,1\} \quad \forall i, j \in n, \forall k \in K \quad \text{Eq. (24)}$$

6.2. The Enhanced ECCRP Model

The enhanced ECCRP (E-ECCRP) model incorporates the same parameters as its predecessor, except for the battery range considerations. It introduces the Electric Cargo Cycle Battery (ECCB) model as a replacement for constraint (19) within the ECCRP framework.

The battery constraints are shown from Eq. (25) through Eq. (27), incorporating the methodology described in Section 3.7.1.3, which includes the computation of slope as per Eq. (12). Eq. (25) is designed to ensure that the initial SoC for each vehicle matches the SoC at the time of departure

from the depot. *Eq. (26)* is tasked with calculating the SoC remaining after a customer visit. This calculation utilizes the *SoC rate* (m_{ijk}) derived from the ECCB model, alongside the distance travelled and the SoC from the preceding customer visit as the starting point for the subsequent customer. *Eq. (27)* specifies that the SoC adjustment occurs only if the customer is visited.

$$SoC_{0k} = y_{1k} \quad \forall k \in K \quad \text{Eq. (25)}$$

$$y_{2ijk} = SoC_{ik} + (m_{ijk} c_{ij} x_{ijk}) \quad \forall i, j, \forall k \in K \quad \text{Eq. (26)}$$

$$SoC_{jk} = y_{2ijk} x_{ijk} \quad \forall i \neq j \quad \text{Eq. (27)}$$

The E-ECCRP has two variants for comparative reasons. The E-ECCRP-1 considers each ECC to have only 1 battery. That way, when comparing with the ECCRP, the pros and cons of the optimization models can be identified. Another variant, as introduced in Section 3.8, is the E-ECCRP-2, which allows the ECCs to have 2 batteries per trip, the one already in the unit, and an extra one to allow battery swapping. The next section shows the results of these comparisons using the optimization scenarios introduced in Section 3.8.1.

The E-ECCRP is presented in two distinct variants for the purpose of comparative analysis. The first variant, E-ECCRP-1, assumes that each ECC is equipped with a single battery. This assumption facilitates a direct comparison with the ECCRP, enabling the identification of advantages and disadvantages between the two optimization models. The second variant, introduced in Section 3.8, is named E-ECCRP-2. This variant permits each ECC to carry two batteries per trip, the one installed in the vehicle and an additional one, thereby enabling the possibility of battery swapping. The next section will discuss the outcomes of the comparative analysis, drawing on the optimization scenarios introduced in Section 3.8.

6.3. Results

Table 21 and Table 22 show the results of the different route optimization scenarios for Ami and Babboe, respectively.

From Table 21 reveals that although the travel distances for Ami did not surpass the battery range specified by the manufacturer, no ECC managed to finish the entire trip on a single battery charge. Consequently, the E-ECCRP-1 approach was impractical for all scenarios. For the E-ECCRP-2, scenario 3 was the only viable option. This scenario, in contrast to the third scenario of the ECCRP

model, needed an additional ECC, and all ECCs had to utilize a second battery to successfully complete the trip.

Table 21: Route Optimization Results - Ami

OS*	OF (km) **	Qty. ***	Distance (km)	Max load (kg)	Total delivered (kg)	Min SoC (%)
ECCRP						
1	92.9	4	25, 28, 25, 15	58, 69, 36, 29	58, 69, 51, 29	-165, -178, -91, -67
2	92.9	4	25, 28, 25, 15	103, 111, 56, 39	103, 111, 71, 39	-152, -232, -166, -53
3	92.1	3	29, 31, 32	35, 36, 69	35, 88, 84	-77, -120, -116
4	92.9	4	25, 28, 25, 15	58, 69, 36, 29	58, 69, 51, 29	-185, -198, -111, -87
5	92.9	4	25, 28, 25, 15	58, 69, 36, 29	58, 69, 51, 29	-215, -228, -141, -117
6	92.9	4	25, 28, 25, 15	58, 69, 36, 29	58, 69, 51, 29	-175, -215, -143, -67
7	NF ****	-	-	-	-	-
8	NF	-	-	-	-	-
9	NF	-	-	-	-	-
10	NF	-	-	-	-	-
11	NF	-	-	-	-	-
12	NF	-	-	-	-	-
E-ECCRP-2						
1	NF	-	-	-	-	-
2	NF	-	-	-	-	-
3	96.8	4	26, 28, 20, 22	43, 58, 40, 36	58, 73, 40, 36	-71, -70, -46, -65
4	NF	-	-	-	-	-
5	NF	-	-	-	-	-
6	NF	-	-	-	-	-
7	NF	-	-	-	-	-
8	NF	-	-	-	-	-
9	NF	-	-	-	-	-
10	NF	-	-	-	-	-
11	NF	-	-	-	-	-
12	NF	-	-	-	-	-

* Optimization Scenarios
 ** Objective Function
 *** Quantity
 **** Not Feasible

Figure 40 shows that the objective function remains consistent across scenarios, with the E-ECCRP-2 having the longest distance at 96.8 km for scenario 3. In contrast, the ECCRP model records the shortest distance for the same scenario at 92.1 km, marginally less than the other trips within this model. Furthermore, scenario 3 under the ECCRP model required fewer units, using 3 compared to the 4 needed in each scenario for other models. The ECCRP model's reliance on metrics other than battery performance means that the number of units and distance per scenario remains unchanged. Only battery consumption varies, which does not limit this particular optimization approach.

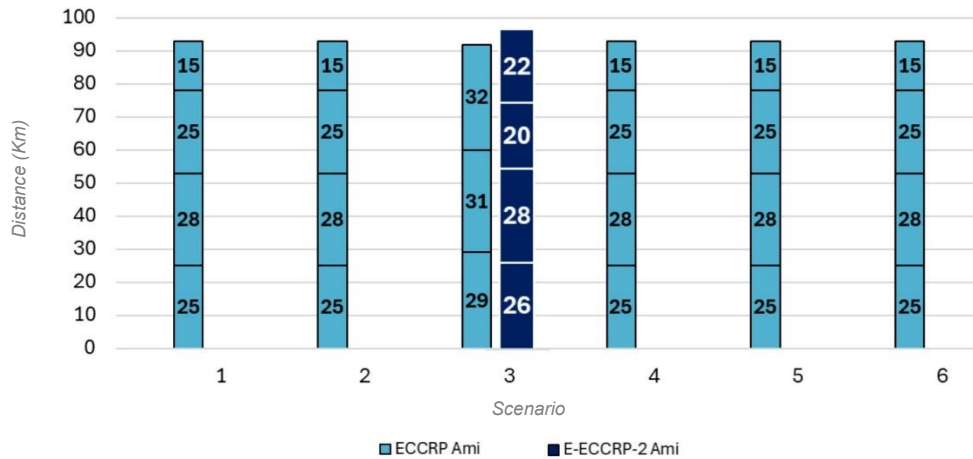


Figure 40: Maximum Distance (km) - Ami

Figure 41 shows the total load delivered by each ECC during the trip. In the ECCRP model, the cargo delivery remains consistent across all scenarios, except scenario 2, which is designated for increased cargo delivery despite using the same number of ECCs. However, Amis deployed in the ECCRP model were unable to finish the trip due to battery depletion. When accounting for the use of two batteries, the number of Amis required increases from 3 to 4, marking this as the only feasible scenario and optimization approach for practical implementation.

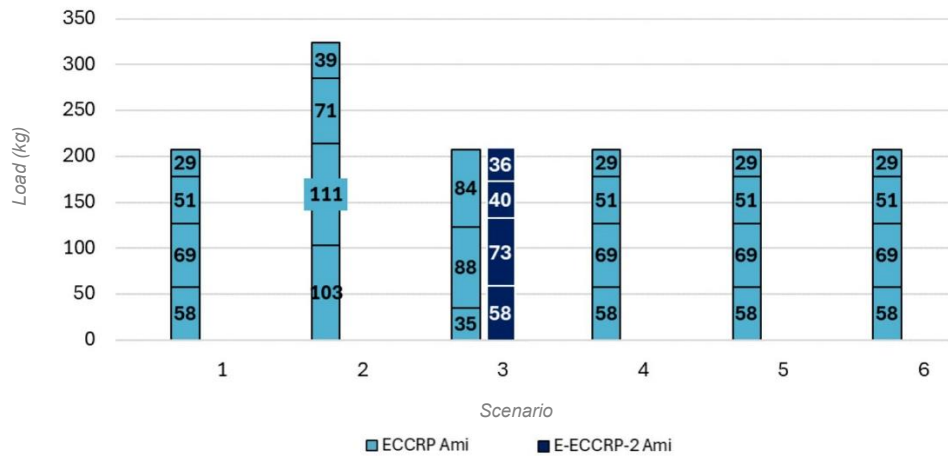


Figure 41: Total Load Delivered (kg) - Ami

The latter is confirmed by Figure 42, which indicates negative SoC levels for the ECCRP model, suggesting that each Ami needs between 2 to 4 batteries to successfully complete the trip.

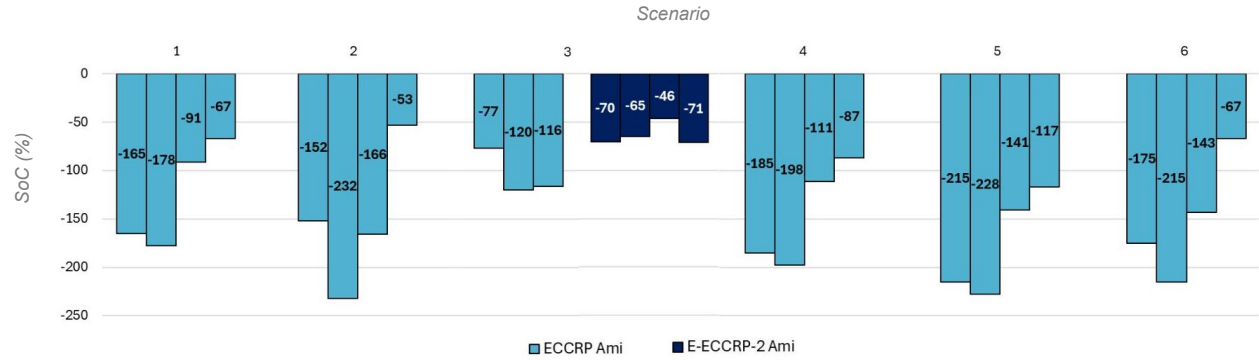


Figure 42: Min SoC - Ami

Table 22 outlines the outcomes of route optimization models for Babboe, offering a more comprehensive analysis compared to Ami, as all scenarios were feasible. In contrast to Ami's performance under the ECCRP model, Babboe scenarios are viable for real-world application, primarily due to its superior battery efficiency highlighted in previous chapters. For instance, the ECCRP model demands between 2 and 5 Babboes to cover all service points at distances of 5 km and 10 km, respectively. Conversely, when applying the ECCB model necessitates only a single Babboe, showcasing a lower objective function, as shown in Figure 43.

Table 22 also illustrates that the distances covered using E-ECCRPs can exceed the manufacturer's recommended maximum range of 75 km. For instance, when servicing customers located 5 km away, the selected unit was able to travel 78 km and still had remaining battery power. Moreover, for customers 10 km away, the distances extended up to 151 km, with battery capacity to spare. This indicates that the manufacturer's specified limits may result in the underutilization of the units.

Table 22: Route Optimization Results - Babboe

OS	OF (km)	Qty.	Distance (km)	Max load (kg)	Total delivered (kg)	Min SoC (%)
ECCRP						
1	87.3	2	47, 40	58, 69	109, 98	86, 88
2	85.6	2	48, 38	93, 94	166, 158	86, 89
3	82.8	2	55, 27	98, 36	139, 68	88, 94
4	87.3	2	47, 40	58, 69	109, 98	66, 68
5	87.3	2	47, 40	58, 69	109, 98	36, 38
6	87.3	2	47, 40	58, 69	109, 98	86, 88
7	199.5	5	42, 30, 45, 42, 40	29, 21, 25, 36, 52	29, 28, 34, 56, 60	88, 91, 87, 88, 89
8	199.5	5	42, 30, 45, 42, 40	39, 33, 45, 54, 77	39, 48, 64, 78, 95	87, 91, 87, 88, 88
9	184.2	4	40, 42, 47, 54	52, 29, 27, 51	58, 29, 42, 78	91, 91, 89, 88
10	199.5	5	42, 30, 45, 42, 40	29, 21, 25, 36, 52	29, 28, 34, 56, 60	68, 71, 67, 68, 69
11	199.5	5	42, 30, 45, 42, 40	29, 21, 25, 36, 52	29, 28, 34, 56, 60	38, 41, 37, 38, 39
12	199.5	5	42, 30, 45, 42, 40	29, 21, 25, 36, 52	29, 28, 34, 56, 60	87, 91, 87, 88, 89

OS	OF (km)	Qty.	Distance (km)	Max load (kg)	Total delivered (kg)	Min SoC (%)
E-ECCRP-1						
1	77.6	1	78	98	207	78
2	78.8	1	79	100	324	76
3	77.6	1	78	98	207	83
4	77.6	1	78	98	207	58
5	77.6	1	78	98	207	28
6	77.6	1	78	98	207	77
7	130.2	1	130	95	207	63
8	151.1	1	151	98	324	55
9	130.2	1	130	95	207	71
10	130.2	1	130	95	207	43
11	128.8	1	129	95	207	13
12	130.2	1	130	95	207	62
E-ECCRP-2						
1	77.6	1	78	98	207	78
2	78.8	1	79	100	324	76
3	77.6	1	78	98	207	83
4	77.6	1	78	98	207	58
5	77.6	1	78	98	207	28
6	77.6	1	78	98	207	77
7	130.2	1	130	95	207	63
8	151.1	1	151	98	324	55
9	130.2	1	130	95	207	71
10	130.2	1	130	95	207	43
11	130.2	1	130	95	207	13
12	130.2	1	130	95	207	62

Figure 43 shows that, for Babboe, the results across all scenarios for both E-ECCRPs remain consistent, except for scenario 11, where the objective function spans 128.84 km for E-ECCRP-1 and 130.2 km for E-ECCRP-2. Interestingly, an increase in demand does not necessarily correlate with a higher objective function in the ECCRP model, which saw a reduction from 87.3 km to 85.6 km. This model observed an uptick in both the maximum load per trip and total delivery, with the SoC maintaining similarity. However, for the E-ECCRPs, the objective function slightly increased from 77.6 km to 78.8 km, alongside a marginal drop in SoC by 2%, despite higher load capacities.

A longer battery range in the ECCRP model resulted in the lowest objective function across scenarios at 82.8 km, with one Babboe handling more cargo than in the baseline scenario, thereby reducing its SoC by an additional 2%. The E-ECCRPs saw minimal impact from enhanced assistance levels, other than an improved SoC from 78% in the baseline to 83%, suggesting that lower assistance levels contribute to better battery conservation during trips.

Figure 44 does not reveal any new information beyond what has already been discussed, except for the expected increase in load delivered as customer demand rises.

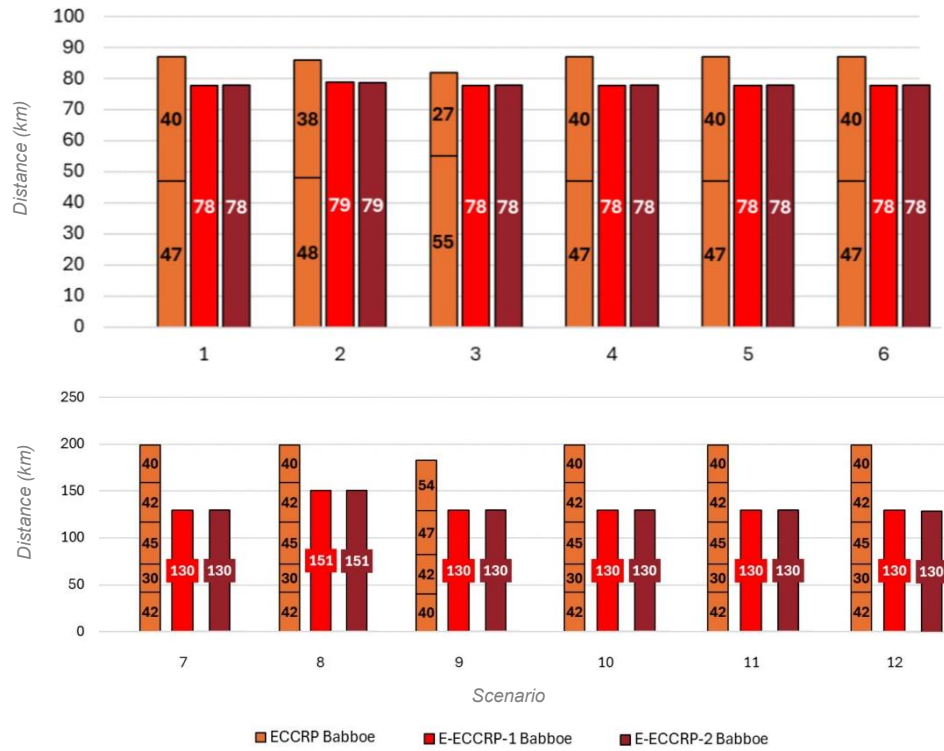


Figure 43: Maximum Distance (km) - Babboe

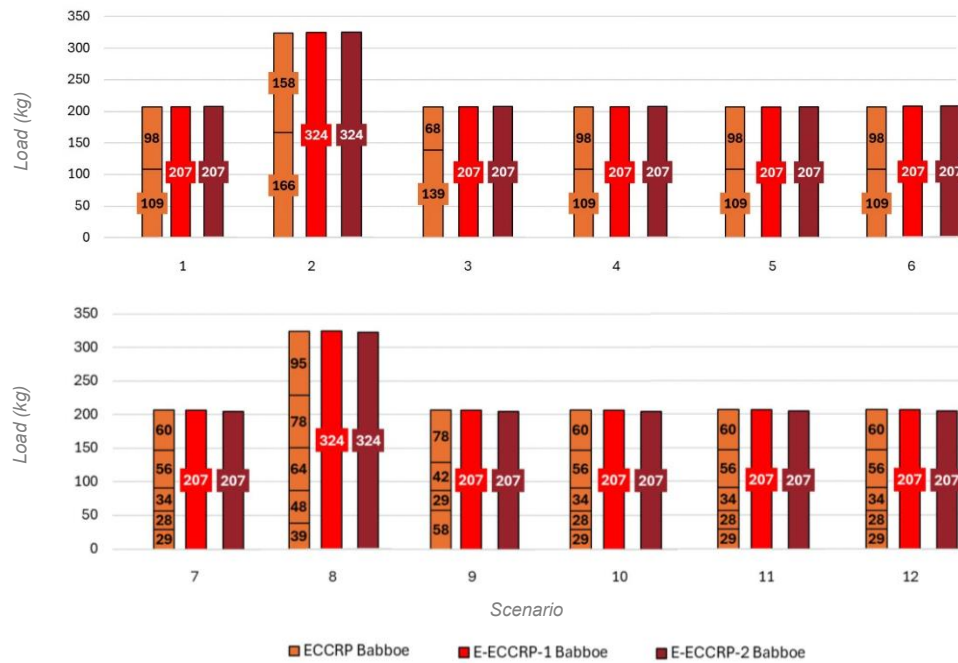


Figure 44: Total Load Delivered (kg) - Babboe

The influence of increased driver weight on the route optimization and final SoC was minimal, indicating just a 1% decrease compared to the baseline scenario. Starting the trip with 80% and 50% battery levels affected only the final SoC as anticipated, with the SoC dropping to 36% for the ECCRP and 28% for the E-ECCRPs. These values further declined to 11% and 13% respectively for longer distances, as shown in Figure 45.

Expanding the service range from 5 km to 10 km around the depot significantly altered the required number of units, jumping from 2 to 5, except in scenario 9, which required only 4 units, doubling the requirement observed in the ECCRP model. Yet, the E-ECCRPs continue to efficiently cover all service points with just one unit, regardless of the increased service range.

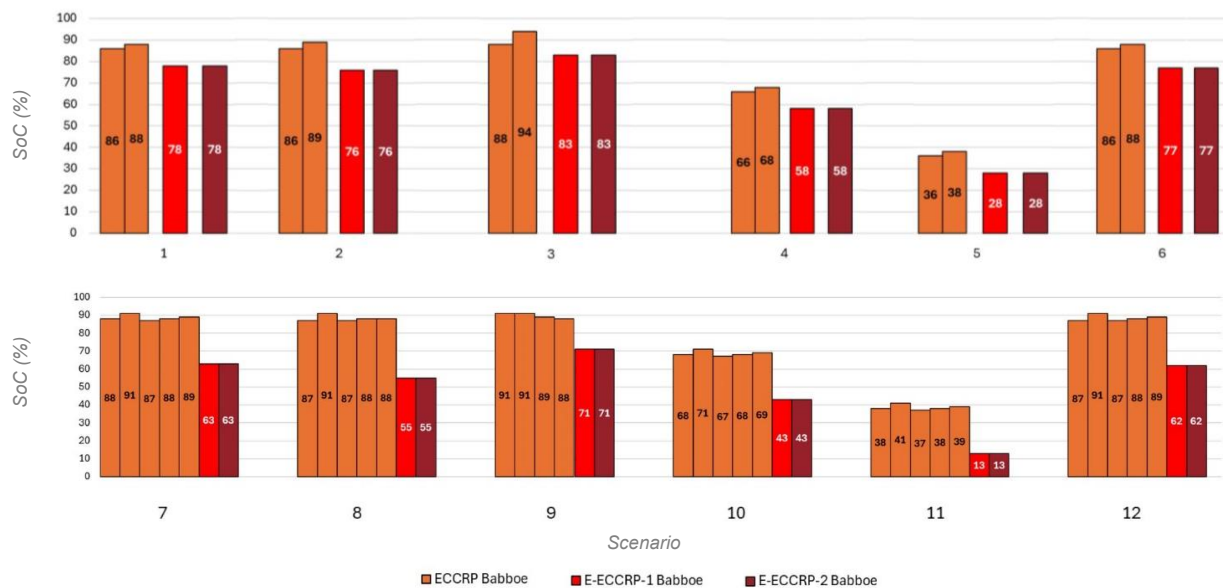


Figure 45: Min SoC (%) - Babboe

Comparing outcomes across the different ECCs, the ECCRP model needs only 4 Amis owing to their superior load capacity, as opposed to the 5 Babboes required for identical route optimization scenarios. It's important to reiterate, however, that despite the reduced number of units, Amis are incapable of finishing their routes due to complete battery exhaustion before returning to the depot. When the strategy involves using two batteries, the scenario still requires 4 Amis, yet for Babboe, a single vehicle suffices, as shown in Figure 46. However, distances exceeding 80 km, with an assumed average speed of 10 km/h, are unlikely to be feasible for a single unit to complete if considering time windows.

Figure 47 illustrates that in the E-ECCRPs, some Babboes transport loads nearly reach their maximum capacity, while in the ECCRP the peak load is 52 kg, which is half of their load capacity. This contrasts with Ami, where the heaviest load carried at any point on the route does not even reach half of its capacity, and in the only practically feasible scenario that includes the use of two batteries, the maximum load does not exceed 58 kg.

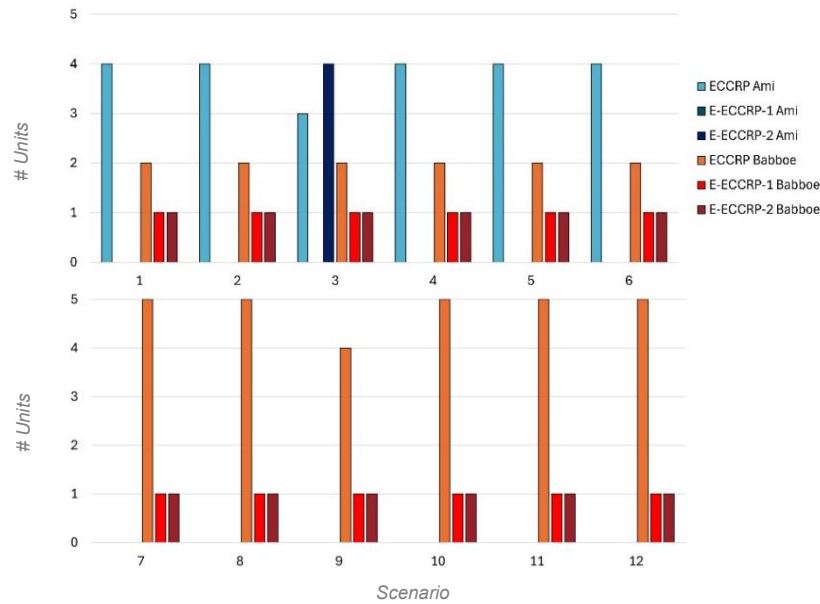


Figure 46: Number of ECCs Required per Scenario

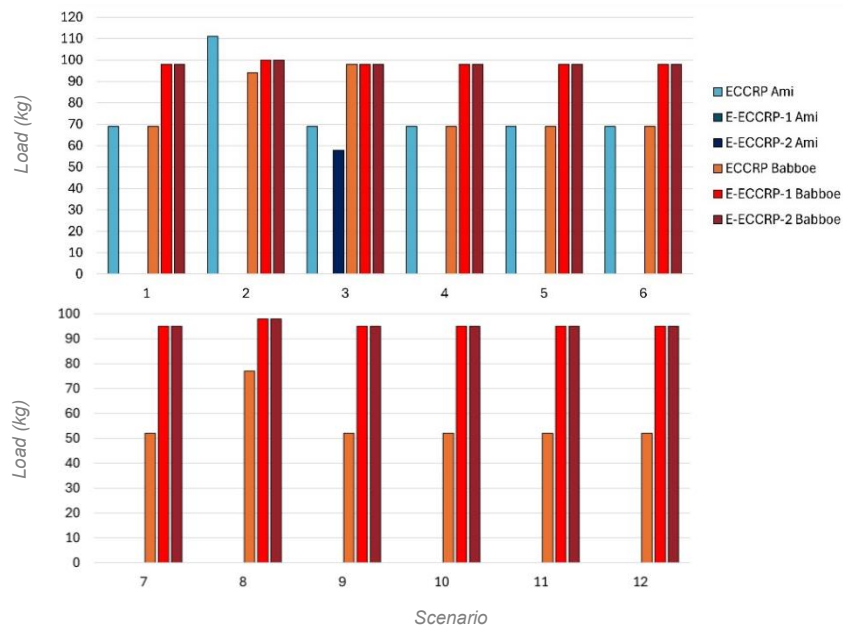


Figure 47: Maximum Load Carried per ECC in Each Scenario (kg)

These findings underscore the efficiency of incorporating the ECCB model into route optimization strategies. Relying solely on manufacturers' specifications can lead to underutilization, needing additional units to service all points as evidenced by Babboe, or overutilization, as observed with Ami, which may not always offer feasible solutions.

Figure 48 and Figure 49 depict the allocation and routing of ECCs for scenario 3 of the E-ECCRP-2 for Ami, and scenario 1 of the E-ECCRP-1 for Babboe, respectively. The routing patterns in these figures appear less structured than the classic Vehicle Routing Problem (VRP) outlined in Figure 39, a variation attributed to the unique constraints applied to ensure the feasibility of each respective scenario.

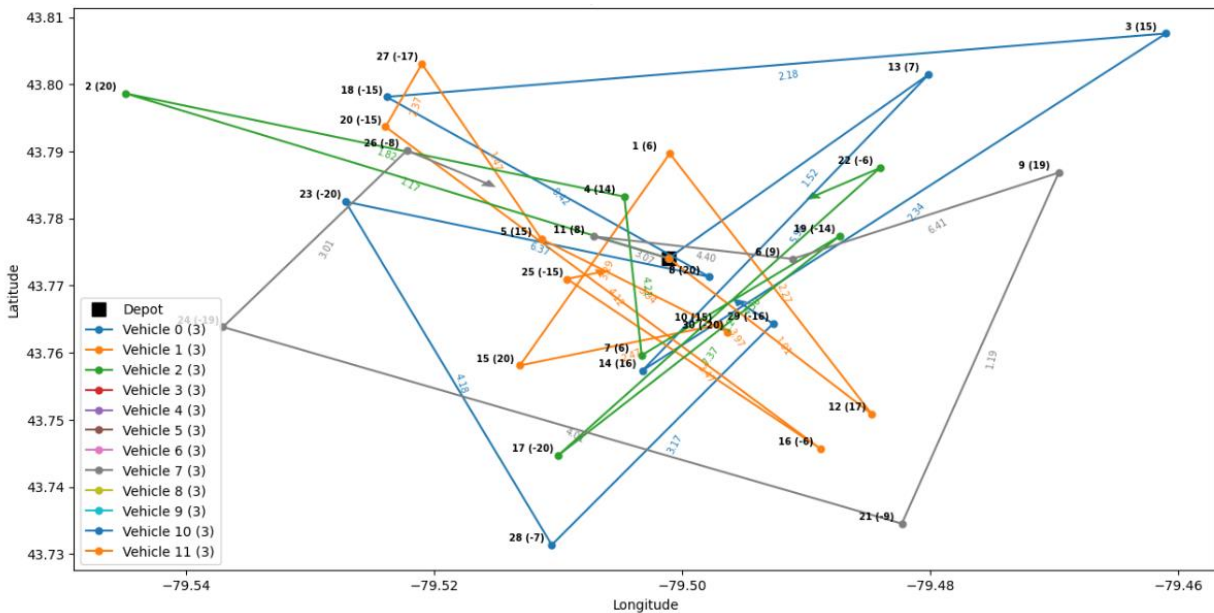
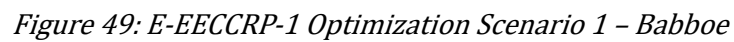


Figure 48: E-ECCRP-2 Optimization Scenario 3 – Ami



The ECCRP is a variation of the Capacitated Vehicle Routing Problem (CVRP), tailored to address the logistics of ECCs by integrating battery capacity constraints alongside load capacity limits. A logistics company deploying ECCs to fulfill delivery or pickup duties from a single depot is the focus. Each ECC is to start fully charged, complete a daily round-trip without subtours, avoid exceeding load or battery capacity, and potentially use multiple batteries. The aim is to meet customer demands cost-effectively, respecting constraints like vehicle load capacity and battery range without specific time windows for deliveries.

The Enhanced ECCRP Model (E-ECCRP) modifies the base model by focusing on battery range flexibility. It introduces the ECCB model to replace the fixed battery range constraint, accounting for varying SoC and enabling strategies like battery swapping. Two variants of this model, E-ECCRP-1 and E-ECCRP-2, are presented for comparative analysis, differing in the number of batteries allowed per trip.

The results, illustrated through tables and figures, compare the performance of two ECCs, Ami and Babboe, under different optimization scenarios. For Ami, the findings indicate limitations in completing routes on a single battery charge, making the E-ECCRP-2 variant, allowing for battery swapping, the only practical approach in certain scenarios. Conversely, Babboe models demonstrate better battery efficiency, making all scenarios feasible with less reliance on additional batteries.

This chapter highlights the efficiency gains from incorporating the ECCB model into route optimization, stressing the balance between load capacity utilization and battery management to ensure all service points are covered effectively.

7. Conclusion

By analyzing ECC performance, developing the Electric Cargo Cycle Battery (ECCB) Model, and exploring the Electric Cargo Cycle Routing Problem (ECCRP), this study has laid a comprehensive foundation for the integration of ECCs into sustainable urban mobility strategies. Although there are also other alternatives such as drones and robots their application is quite limited (Yuen et al., 2022; Aurambout et al., 2019, Goodchild & Toy, 2018).

The conclusions drawn from this research underscore the viability and efficiency of ECCs as a green transportation solution, highlighting several key findings and implications for future urban logistics operations.

Firstly, the detailed analysis of the Ami and Babboe explains the critical factors influencing battery and operational performance. Through the application of non-linear statistical methods, the research reveals how assistance levels, extra weight, total weight, and distance, play pivotal roles in determining the consumption rate of the battery (SoC rate). Contrary to widespread claims in the literature, neither average slope nor speed significantly affects battery performance. These insights are instrumental in guiding the development of best practices for ECC usage, ensuring optimal performance and longevity of the battery systems.

The introduction and validation of the ECCB Model mark a significant advancement in predicting and optimizing ECC battery performance. By leveraging statistical and machine learning methodologies, this model provides accurate forecasts of battery consumption under various operational conditions.

Furthermore, the exploration of the ECCRP, particularly through the development of the Enhanced ECCRP (E-ECCRP) models, offers a novel approach to addressing the logistics optimization challenges specific to ECCs. The comparative analysis of different routing scenarios demonstrates the practical implications of battery optimization on route planning, highlighting the potential of the E-ECCRP Model to transform ECC deployment strategies as a practical tool for logistics companies looking to harness the benefits of ECCs in their operations.

To generalize the findings from this thesis, further research is necessary because only two specific versions of ECCs were evaluated, limiting the reliability of the models to those versions under the current conditions of additional weight, temperature, and road characteristics. Additional data should be collected for extra weight ranging from 0 kg to 50 kg, along with more variations in terrain and seasons. This will allow for a broader range of temperature values to assess the impact

more accurately on battery performance. The scope of this additional testing was constrained by the time limitations of completing a master's degree and the availability of resources.

As cities worldwide continue to seek sustainable transportation solutions, ECCs emerge as a promising option for urban logistics. This study not only deepens the understanding of ECC performance and optimization but also sets the stage for further research and development in this field.

Future research in this area should expand to encompass a broader array of ECC designs from across the market, alongside diverse user profiles, and urban environments. Examining constraints for the volume dimensions of the cargo box and the packages transported could yield insights into whether the ECC's capacity meets demand without overfilling. Another important aspect is the simulation of the model in commercial software, providing a baseline for comparison with the results of this thesis. Although this may require expertise beyond the current scope, it is achievable with future efforts. Finally, future studies could explore the impact of urban infrastructure on ECC routing, and the scalability of ECC deployment in larger logistics networks. Ultimately, the journey towards sustainable urban mobility is multifaceted, requiring continued innovation, collaboration, and commitment to green transportation solutions like ECCs.

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Appendices

Appendix A: Service Points for Route Optimization Scenarios

Table 23: Service Points at 5 km from the Depot and Demand of 5 kg to 20 kg

Id	Latitude	Longitude	Service	Demand
1	43.789681	-79.50102	pickup	6
2	43.798642	-79.544909	pickup	20
3	43.807572	-79.460999	pickup	15
4	43.783268	-79.504684	pickup	14
5	43.776945	-79.511379	pickup	15
6	43.773985	-79.491125	pickup	9
7	43.759624	-79.503291	pickup	6
8	43.771306	-79.497827	pickup	20
9	43.78683	-79.469652	pickup	19
10	43.764172	-79.497081	pickup	15
11	43.777335	-79.507118	pickup	8
12	43.750879	-79.484737	pickup	17
13	43.801449	-79.480152	pickup	7
14	43.757336	-79.503232	pickup	16
15	43.758105	-79.513104	pickup	20
16	43.745712	-79.488883	delivery	6
17	43.744662	-79.51005	delivery	20
18	43.798131	-79.523865	delivery	15
19	43.777386	-79.487323	delivery	14
20	43.793665	-79.523946	delivery	15
21	43.734539	-79.482304	delivery	9
22	43.787532	-79.484071	delivery	6
23	43.782511	-79.527175	delivery	20
24	43.763837	-79.537053	delivery	19
25	43.770998	-79.509312	delivery	15
26	43.79014	-79.522228	delivery	8
27	43.803053	-79.521009	delivery	17
28	43.731363	-79.51054	delivery	7
29	43.764343	-79.492692	delivery	16
30	43.763091	-79.496373	delivery	20

Table 24: Service Points at 5 km from the Depot and Demand of 5 kg to 30 kg

Id	Latitude	Longitude	Service	Demand
1	43.789681	-79.50102	pickup	26
2	43.798642	-79.54491	pickup	24
3	43.807572	-79.461	pickup	25
4	43.783268	-79.50468	pickup	14
5	43.776945	-79.51138	pickup	15
6	43.773985	-79.49113	pickup	19
7	43.759624	-79.50329	pickup	16
8	43.771306	-79.49783	pickup	28
9	43.78683	-79.46965	pickup	19
10	43.764172	-79.49708	pickup	25
11	43.777335	-79.50712	pickup	18
12	43.750879	-79.48474	pickup	27
13	43.801449	-79.48015	pickup	17
14	43.757336	-79.50323	pickup	26
15	43.758105	-79.5131	pickup	25
16	43.745712	-79.48888	delivery	26
17	43.744662	-79.51005	delivery	24
18	43.798131	-79.52387	delivery	25
19	43.777386	-79.48732	delivery	14
20	43.793665	-79.52395	delivery	15
21	43.734539	-79.4823	delivery	19
22	43.787532	-79.48407	delivery	16
23	43.782511	-79.52718	delivery	28
24	43.763837	-79.53705	delivery	19
25	43.770998	-79.50931	delivery	25
26	43.79014	-79.52223	delivery	18
27	43.803053	-79.52101	delivery	27
28	43.731363	-79.51054	delivery	17
29	43.764343	-79.49269	delivery	26
30	43.763091	-79.49637	delivery	25

Table 25: Service Points at 10 km from the Depot and Demand of 5 kg to 20 kg

Id	Latitude	Longitude	Service	Demand
1	43.700422	-79.44138	pickup	6
2	43.835375	-79.55796	pickup	20
3	43.705064	-79.56452	pickup	15
4	43.791064	-79.40111	pickup	14
5	43.726209	-79.54464	pickup	15
6	43.747052	-79.49535	pickup	9
7	43.760501	-79.48331	pickup	6
8	43.785914	-79.50255	pickup	20
9	43.825397	-79.44843	pickup	19
10	43.823791	-79.40363	pickup	15
11	43.764017	-79.45439	pickup	8
12	43.77788	-79.49532	pickup	17
13	43.752308	-79.54175	pickup	7
14	43.73821	-79.55138	pickup	16
15	43.723157	-79.44839	pickup	20
16	43.769805	-79.51308	delivery	6
17	43.814199	-79.53707	delivery	20
18	43.736825	-79.5351	delivery	15
19	43.782983	-79.52383	delivery	14
20	43.77782	-79.49769	delivery	15
21	43.769826	-79.52828	delivery	9
22	43.741774	-79.48166	delivery	6
23	43.845469	-79.56683	delivery	20
24	43.696069	-79.46421	delivery	19
25	43.82201	-79.54072	delivery	15
26	43.744851	-79.43437	delivery	8
27	43.720074	-79.57194	delivery	17
28	43.744667	-79.52984	delivery	7
29	43.820638	-79.59335	delivery	16
30	43.740827	-79.6046	delivery	20

Table 26: Service Points at 10 km from the Depot and Demand of 5 kg to 30 kg

Id	Latitude	Longitude	Service	Demand
1	43.700422	-79.44138	pickup	26
2	43.835375	-79.55796	pickup	24
3	43.705064	-79.56452	pickup	25
4	43.791064	-79.40111	pickup	14
5	43.726209	-79.54464	pickup	15
6	43.747052	-79.49535	pickup	19
7	43.760501	-79.48331	pickup	16
8	43.785914	-79.50255	pickup	28
9	43.825397	-79.44843	pickup	19
10	43.823791	-79.40363	pickup	25
11	43.764017	-79.45439	pickup	18
12	43.77788	-79.49532	pickup	27
13	43.752308	-79.54175	pickup	17
14	43.73821	-79.55138	pickup	26
15	43.723157	-79.44839	pickup	25
16	43.769805	-79.51308	delivery	26
17	43.814199	-79.53707	delivery	24
18	43.736825	-79.5351	delivery	25
19	43.782983	-79.52383	delivery	14
20	43.77782	-79.49769	delivery	15
21	43.769826	-79.52828	delivery	19
22	43.741774	-79.48166	delivery	16
23	43.845469	-79.56683	delivery	28
24	43.696069	-79.46421	delivery	19
25	43.82201	-79.54072	delivery	25
26	43.744851	-79.43437	delivery	18
27	43.720074	-79.57194	delivery	27
28	43.744667	-79.52984	delivery	17
29	43.820638	-79.59335	delivery	26
30	43.740827	-79.6046	delivery	25

Appendix B: Python Codes for RF, ECCRP, E-ECCRP-1 and E-ECCRP-2

Random Forest (RF)

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor

class RandomForestModel:
    def __init__(self, data_path):
        self.data_path = data_path
        self.model = None

    def load_data(self):
        # Load dataset
        df = pd.read_excel(self.data_path)
        # Specify features and target variable
        features = ['Extra_Weight_kg', 'Total_Weight_kg', 'Assistance_Level']
        X = df[features]
        y = df['percent_soc']
        return train_test_split(X, y, test_size=0.2, random_state=42)

    def train_model(self, n_estimators, max_depth):
        X_train, X_test, y_train, y_test = self.load_data()
        # Use specified parameters for RandomForestRegressor
        self.model = RandomForestRegressor(n_estimators=n_estimators,
max_depth=max_depth, random_state=42)
        self.model.fit(X_train, y_train)

    def predict(self, X):
        if self.model:
            return self.model.predict(X)
        else:
            print("Model is not trained.")
            return None
```

ECCRP

```
"""Electric Cargo Cycle Routing Problem (ECCRP)."""
import pandas as pd
import json
from Random Forest (RF) import RandomForestModel
from ortools.constraint_solver import routing_enums_pb2
from ortools.constraint_solver import pywrapcp

def create_data_model(distance_matrix, demands, vehicle_capacities,
vehicle_battery_capacities, num_vehicles, demands_del_per_vehicle,
demands_pic_per_vehicle, pred_const, sequence_per_vehicle, extra_per_vehicle,
initial_soc, max_dist, pickups_deliveries, distance_real):

    """Stores the data for the problem."""
    data = {}
    data['distance_matrix'] = distance_matrix
```

```

data['demands'] = demands
data['vehicle_capacities'] = vehicle_capacities
data['vehicle_battery_capacities'] = vehicle_battery_capacities
data['num_vehicles'] = num_vehicles
data['depot'] = 0
data['demands_del'] = demands_del_per_vehicle
data['demands_pic'] = demands_pic_per_vehicle
data['pred_const'] = pred_const
data['sequence'] = sequence_per_vehicle
data['extra'] = extra_per_vehicle
data['initial_soc'] = initial_soc
data['max_dist'] = max_dist
data['pickups_deliveries'] = pickups_deliveries
data['distance_real'] = distance_real

return data

def main():
    """Entry point of the program."""

    # Instantiate the data problem.
    distance_matrix_file_path = 'path/distance_matrix.json'

    # Load customer data
    customer_data = 'path/service_points.xlsx'
    customers_df = pd.read_excel(customer_data)

    # Load ECCs information
    ecc_file_path = 'path/vehicle_list.xlsx'
    df_ecc = pd.read_excel(ecc_file_path)

    # Extract ecc_models information along with initial_soc and additional
    data for feature vector
    ecc_models = {}
    for index, row in df_ecc.iterrows():
        if row['availability'] == 'yes':
            ecc_models[row['vehicle_id']] = {
                'load_capacity': row['load_capacity'],
                'driver_weight': row['driver_weight'],
                'ecc_weight': row['ecc_weight'],
                'assistance_level': row['assistance_level'],
                'max_dist': row['max_dist'],
                'initial_soc': row['initial_soc'],
                'model': row['model']
            }

    vehicle_ids = list(ecc_models.keys())

    # Depot Location
    depot_location = (43.774076, -79.501122)

    # Load the distance matrix from the JSON file
    def build_rounded_distance_matrix(distance_matrix_file_path):
        # Load the distance matrix from the JSON file
        with open(distance_matrix_file_path, 'r') as f:
            distance_matrix1 = json.load(f)

```

```

        distance_matrix = []
        for row in distance_matrix1:
            rounded_row = [round(distance) for distance in row]
            distance_matrix.append(rounded_row)

        return distance_matrix

    distance_matrix =
build_rounded_distance_matrix(distance_matrix_file_path)

    with open(distance_matrix_file_path, 'r') as f:
        distance_matrix2 = json.load(f)

    distance_real = [[float(round(distance,2)) for distance in row] for row
in distance_matrix2]

    pickups_deliveries = [[1, 16], [2, 17], [3, 18], [4, 19], [5, 20], [6,
21], [7, 22], [8, 23], [9, 24], [10, 25], [11, 26], [12, 27], [13, 28], [14,
29], [15, 30]]

    demands = [-row['demand'] if row['service'] == 'delivery' else
row['demand'] for index, row in customers_df.iterrows()]
    demands.insert(0, 0) # Insert 0 at the beginning for the depot

    vehicle_capacities = [model['load_capacity'] for model in
ecc_models.values()]
    vehicle_battery_capacities = [model['initial_soc'] for model in
ecc_models.values()]
    num_vehicles = len(ecc_models)
    initial_soc = [model['initial_soc'] for model in ecc_models.values()]
    max_dist = [model['max_dist'] for model in ecc_models.values()]

    rf_models = {}
    pred_const = {}
    model_paths = {
        'Ami': 'path/data - Ami.xlsx',
        'Babboe': 'path/data - Babboe.xlsx',
    }

    demands_del_per_vehicle = {}
    demands_pic_per_vehicle = {}
    sequence_per_vehicle = {}
    extra_per_vehicle = {}

    for vehicle_id, model_info in ecc_models.items():

        demands_del = [-row['demand'] if row['service'] == 'delivery' else 0
for _, row in customers_df.iterrows()]
        demands_del.insert(0, 0) # Insert 0 at the beginning for the depot

        demands_pic = [0 if row['service'] == 'delivery' else row['demand']
for _, row in customers_df.iterrows()]
        demands_pic.insert(0, 0)

        extra = [p + d for p, d in zip(demands_pic, demands_del)]
        extra2 = extra[1:]

```

```

sequence = [0]
# Loop through extra2 to calculate subsequent elements in the
sequence for each vehicle
for value in extra2:
    sequence.append(sequence[-1] + value)

# Store the calculated lists in the dictionaries
demands_del_per_vehicle[vehicle_id] = demands_del
demands_pic_per_vehicle[vehicle_id] = demands_pic
extra_per_vehicle[vehicle_id] = extra
sequence_per_vehicle[vehicle_id] = sequence

model_type = model_info['model']

ecc = [[model['ecc_weight'] for model in ecc_models.values()][0]] *
len(sequence)
driver = [[model['driver_weight'] for model in
ecc_models.values()][0]] * len(sequence)
total_weight = [e + r + d for e, r, d in zip(sequence, ecc, driver)]
assistance = [[model['assistance_level'] for model in
ecc_models.values()][0]] * len(sequence)

# Check if the model type is recognized and set parameters
accordingly
if model_type == 'Ami':
    rf_model_path = model_paths['Ami']
    n_estimators = 200
    max_depth = 10
elif model_type == 'Babboe':
    rf_model_path = model_paths['Babboe']
    n_estimators = 200
    max_depth = 5
else:
    # Fallback or default values
    print(f"Warning: Model type {model_type} not recognized. Please
check.")
    continue # Skip this iteration

# Create the RandomForestModel instance with the determined path
rf_model = RandomForestModel(rf_model_path)

# Train the model with the determined parameters
rf_model.train_model(n_estimators=n_estimators, max_depth=max_depth)

# Store the trained model in the dictionary with vehicle_id as key
rf_models[vehicle_id] = rf_model

# Prepare the features for prediction
X_feature = pd.DataFrame({
    'Extra_Weight_kg': sequence,
    'Total_Weight_kg': total_weight,
    'Assistance_Level': assistance
})

# Predict using the trained model and store the predictions
pred_const[vehicle_id] = rf_model.predict(X_feature)

```

```

# Modify the data creation to include this new list
data = create_data_model(distance_matrix, demands, vehicle_capacities,
vehicle_battery_capacities, num_vehicles, demands_del_per_vehicle,
demands_pic_per_vehicle,
                        pred_const, sequence_per_vehicle, extra_per_vehicle,
initial_soc, max_dist, pickups_deliveries, distance_real)

# Create the routing index manager.
manager = pywrapcp.RoutingIndexManager(
    len(data["distance_matrix"]), data["num_vehicles"], data["depot"]
)

# Create Routing Model.
routing = pywrapcp.RoutingModel(manager)

# Define cost of each arc.
def distance_callback(from_index, to_index):
    """Returns the manhattan distance between the two nodes."""
    # Convert from routing variable Index to distance matrix NodeIndex.
    from_node = manager.IndexToNode(from_index)
    to_node = manager.IndexToNode(to_index)
    return data["distance_matrix"][from_node][to_node]

transit_callback_index =
routing.RegisterTransitCallback(distance_callback)
routing.SetArcCostEvaluatorOfAllVehicles(transit_callback_index)

# Add Distance constraint.
dimension_name = "Distance"
routing.AddDimensionWithVehicleCapacity(
    transit_callback_index,
    0, # no slack
    data['max_dist'], # vehicle maximum travel distance
    True, # start cumul to zero
    dimension_name,
)
distance_dimension = routing.GetDimensionOrDie(dimension_name)
#distance_dimension.SetGlobalSpanCostCoefficient(100)

# Add Capacity constraint.
def demand_callback(from_index, to_index):
    """Returns the demand of the node."""
    from_node = manager.IndexToNode(from_index)
    to_node = manager.IndexToNode(to_index)
    et=data['demands'][from_node]
    return et

demand_callback_index = routing.RegisterTransitCallback(demand_callback)

routing.AddDimensionWithVehicleCapacity(
    demand_callback_index,
    0, # null capacity slack
    data['vehicle_capacities'], # vehicle maximum capacities
    True, # start cumul to zero
    'Capacity')

```

```

# Define Transportation Requests.
for request in data["pickups_deliveries"]:
    pickup_index = manager.NodeToIndex(request[0])
    delivery_index = manager.NodeToIndex(request[1])
    routing.AddPickupAndDelivery(pickup_index, delivery_index)
    routing.solver().Add(
        routing.VehicleVar(pickup_index) ==
routing.VehicleVar(delivery_index)
    )

# Setting first solution heuristic.
search_parameters = pywrapcp.DefaultRoutingSearchParameters()
search_parameters.first_solution_strategy =
(routing_enums_pb2.FirstSolutionStrategy.PATH_CHEAPEST_ARC)
search_parameters.local_search_metaheuristic =
(routing_enums_pb2.LocalSearchMetaheuristic.GUIDED_LOCAL_SEARCH)
search_parameters.time_limit.seconds = 150

# Solve the problem.
solution = routing.SolveWithParameters(search_parameters)

# Print solution on console.
if solution:
    print_solution(data, manager, routing, solution, ecc_models,
vehicle_ids)
    print(data['distance_matrix'])
    print(data['distance_real'])

    vehicle_model_assignments = [ecc_models[i]['assistance_level'] for i
in range(num_vehicles)]

    plotter = PlotRoutes(solution, manager, routing, depot_location,
vehicle_model_assignments, data['distance_real'], customers_df)

    title = "ECCRP - Base Model - Optimization Scenario 2 - Ami" #
Define your custom title here
    plotter.plot(title=title)

def print_solution(data, manager, routing, solution, ecc_models,
vehicle_ids):
    """Prints solution on console."""
    print(f"Objective: {solution.ObjectiveValue()}")
    total_distance = 0
    for vehicle_id in range(data["num_vehicles"]):
        index = routing.Start(vehicle_id)
        vehicle_id_key = vehicle_ids[vehicle_id] # Get the correct vehicle
ID key from the list
        vehicle_model = ecc_models[vehicle_id_key]['model']
        plan_output = f"Route for vehicle {vehicle_id} ({vehicle_model}):\n"

        route_distance = 0
        t_deli = 0 # Initialize total deliveries for the vehicle
        t_pickups = 0 # Initialize total pickups for the vehicle
        cumulative_demand = 0 # Initialize cumulative demand
        max_cumulative_demand = 0

        # Assuming each vehicle's initial SOC is stored in

```

```

data['vehicle_battery_capacities'][vehicle_id]
    initial_soc = data['vehicle_battery_capacities'][vehicle_id]
    y1 = [initial_soc] # Initialize list to hold cumulative y_2 values

    previous_node = -1

    while not routing.IsEnd(index):
        node_index = manager.IndexToNode(index)
        if node_index != previous_node: # Add node if it's different
from the previous one
            plan_output += f" {node_index} ->"
            previous_node = node_index

        previous_index = index
        index = solution.Value(routing.NextVar(index))
        #route_distance += routing.GetArcCostForVehicle(previous_index,
index, vehicle_id)

        if not routing.IsEnd(index):
            distance =
data['distance_real'][manager.IndexToNode(previous_index)][manager.IndexToNode(index)]

            route_distance += distance
            t_pickups +=
data["demands_pic"][vehicle_id_key][manager.IndexToNode(index)]
            t_deliveries +=
data["demands_del"][vehicle_id_key][manager.IndexToNode(index)]

            # Update cumulative demand and check if it's the maximum
cumulative_demand +=
(data["demands_pic"][vehicle_id_key][manager.IndexToNode(index)] +
data["demands_del"][vehicle_id_key][manager.IndexToNode(index)])
            max_cumulative_demand = max(max_cumulative_demand,
abs(cumulative_demand))

            m =
data['pred_const'][vehicle_id_key][manager.IndexToNode(index)]
            y2 = y1[-1] + m * distance * 1000
            y1.append(y2)

        plan_output = plan_output.rstrip('->') + f" -> 0"
        plan_output += f"\nTotal distance: {route_distance:.2f}km\n" + \
            f"Total delivered: {t_pickups} kg, Max load:
{max_cumulative_demand} kg\n" + \
            f"SoC: [{', '.join(f'{x:.2f}' for x in y1)}]\n"

        print(plan_output)
        total_distance += route_distance

    print(f"Total distance of all routes: {total_distance}km")

if __name__ == "__main__":
    main()

```

E-ECCRP-1

```
"""Enhanced Electric Cargo Cycle Routing Problem with 1 Battery (E-ECCRP-1)"""
import pandas as pd
import json
from Random Forest (RF) import RandomForestModel
from ortools.constraint_solver import routing_enums_pb2
from ortools.constraint_solver import pywrapcp

def create_data_model(distance_matrix, demands, vehicle_capacities,
vehicle_battery_capacities, num_vehicles, demands_del_per_vehicle,
demands_pic_per_vehicle, pred_const, sequence_per_vehicle, extra_per_vehicle,
initial_soc, max_dist, pickups_deliveries, distance_real):

    """Stores the data for the problem."""
    data = {}
    data['distance_matrix'] = distance_matrix
    data['demands'] = demands
    data['vehicle_capacities'] = vehicle_capacities
    data['vehicle_battery_capacities'] = vehicle_battery_capacities
    data['num_vehicles'] = num_vehicles
    data['depot'] = 0
    data['demands_del'] = demands_del_per_vehicle
    data['demands_pic'] = demands_pic_per_vehicle
    data['pred_const'] = pred_const
    data['sequence'] = sequence_per_vehicle
    data['extra'] = extra_per_vehicle
    data['initial_soc'] = initial_soc
    data['max_dist'] = max_dist
    data['pickups_deliveries'] = pickups_deliveries
    data['distance_real'] = distance_real

    return data

def main():
    """Entry point of the program."""

    # Instantiate the data problem.
    distance_matrix_file_path = 'path/distance_matrix.json'

    # Load customer data
    customer_data = 'path/service_points.xlsx'
    customers_df = pd.read_excel(customer_data)

    # Load ECCs information
    ecc_file_path = 'path/vehicle_list.xlsx'
    df_ecc = pd.read_excel(ecc_file_path)

    # Extract ecc_models information along with initial_soc and additional
    data for feature vector
    ecc_models = {}
    for index, row in df_ecc.iterrows():
        if row['availability'] == 'yes':
            ecc_models[row['vehicle_id']] = {
                'load_capacity': row['load_capacity'],
```

```

        'driver_weight': row['driver_weight'],
        'ecc_weight': row['ecc_weight'],
        'assistance_level': row['assistance_level'],
        'max_dist': row['max_dist'],
        'initial_soc': row['initial_soc'],
        'model': row['model']
    }

vehicle_ids = list(ecc_models.keys())

# Depot Location
depot_location = (43.774076, -79.501122)

# Load the distance matrix from the JSON file
def build_rounded_distance_matrix(distance_matrix_file_path):
    # Load the distance matrix from the JSON file
    with open(distance_matrix_file_path, 'r') as f:
        distance_matrix1 = json.load(f)

    distance_matrix = []
    for row in distance_matrix1:
        rounded_row = [round(distance) for distance in row]
        distance_matrix.append(rounded_row)

    return distance_matrix

distance_matrix =
build_rounded_distance_matrix(distance_matrix_file_path)

    with open(distance_matrix_file_path, 'r') as f:
        distance_matrix2 = json.load(f)

    distance_real = [[float(round(distance,2)) for distance in row] for row
in distance_matrix2]

    pickups_deliveries = [[1, 16], [2, 17], [3, 18], [4, 19], [5, 20], [6,
21], [7, 22], [8, 23], [9, 24], [10, 25], [11, 26], [12, 27], [13, 28], [14,
29], [15, 30]]

    demands = [-row['demand'] if row['service'] == 'delivery' else
row['demand'] for index, row in customers_df.iterrows()]
    demands.insert(0, 0) # Insert 0 at the beginning for the depot

    vehicle_capacities = [model['load_capacity'] for model in
ecc_models.values()]
    vehicle_battery_capacities = [model['initial_soc'] for model in
ecc_models.values()]
    num_vehicles = len(ecc_models)
    initial_soc = [model['initial_soc'] for model in ecc_models.values()]
    max_dist = [model['max_dist'] for model in ecc_models.values()]

    rf_models = {}
    pred_const = {}
    model_paths = {
        'Ami': 'path/data - Ami.xlsx',
        'Babboe': 'path/data - Babboe.xlsx',
    }
}

```

```

demands_del_per_vehicle = {}
demands_pic_per_vehicle = {}
sequence_per_vehicle = {}
extra_per_vehicle = {}

for vehicle_id, model_info in ecc_models.items():

    demands_del = [-row['demand'] if row['service'] == 'delivery' else 0
for _, row in customers_df.iterrows()]
    demands_del.insert(0, 0) # Insert 0 at the beginning for the depot

    demands_pic = [0 if row['service'] == 'delivery' else row['demand']
for _, row in customers_df.iterrows()]
    demands_pic.insert(0, 0)

    extra = [p + d for p, d in zip(demands_pic, demands_del)]
    extra2 = extra[1:]

    sequence = [0]
    # Loop through extra2 to calculate subsequent elements in the
sequence for each vehicle
    for value in extra2:
        sequence.append(sequence[-1] + value)

    # Store the calculated lists in the dictionaries
    demands_del_per_vehicle[vehicle_id] = demands_del
    demands_pic_per_vehicle[vehicle_id] = demands_pic
    extra_per_vehicle[vehicle_id] = extra
    sequence_per_vehicle[vehicle_id] = sequence

    model_type = model_info['model']

    ecc = [[model['ecc_weight'] for model in ecc_models.values()][0]] *
len(sequence)
    driver = [[model['driver_weight'] for model in
ecc_models.values()][0]] * len(sequence)
    total_weight = [e + r + d for e, r, d in zip(sequence, ecc, driver)]
    assistance = [[model['assistance_level'] for model in
ecc_models.values()][0]] * len(sequence)

    # Check if the model type is recognized and set parameters
accordingly
    if model_type == 'Ami':
        rf_model_path = model_paths['Ami']
        n_estimators = 200
        max_depth = 10
    elif model_type == 'Babboe':
        rf_model_path = model_paths['Babboe']
        n_estimators = 200
        max_depth = 5
    else:
        # Fallback or default values
        print(f"Warning: Model type {model_type} not recognized. Please
check.")
        continue # Skip this iteration

```

```

# Create the RandomForestModel instance with the determined path
rf_model = RandomForestModel(rf_model_path)

# Train the model with the determined parameters
rf_model.train_model(n_estimators=n_estimators, max_depth=max_depth)

# Store the trained model in the dictionary with vehicle_id as key
rf_models[vehicle_id] = rf_model

# Prepare the features for prediction
X_feature = pd.DataFrame({
    'Extra_Weight_kg': sequence,
    'Total_Weight_kg': total_weight,
    'Assistance_Level': assistance
})

# Predict using the trained model and store the predictions
pred_const[vehicle_id] = rf_model.predict(X_feature)

# Modify the data creation to include this new list
data = create_data_model(distance_matrix, demands, vehicle_capacities,
vehicle_battery_capacities, num_vehicles, demands_del_per_vehicle,
demands_pic_per_vehicle,
                        pred_const, sequence_per_vehicle, extra_per_vehicle,
initial_soc, max_dist, pickups_deliveries, distance_real)

# Create the routing index manager.
manager = pywrapcp.RoutingIndexManager(
    len(data["distance_matrix"]), data["num_vehicles"], data["depot"]
)

# Create Routing Model.
routing = pywrapcp.RoutingModel(manager)

# Define cost of each arc.
def distance_callback(from_index, to_index):
    """Returns the manhattan distance between the two nodes."""
    # Convert from routing variable Index to distance matrix NodeIndex.
    from_node = manager.IndexToNode(from_index)
    to_node = manager.IndexToNode(to_index)
    return data["distance_matrix"][from_node][to_node]

transit_callback_index =
routing.RegisterTransitCallback(distance_callback)
routing.SetArcCostEvaluatorOfAllVehicles(transit_callback_index)

# Add Capacity constraint.
def demand_callback(from_index, to_index):
    """Returns the demand of the node."""
    from_node = manager.IndexToNode(from_index)
    to_node = manager.IndexToNode(to_index)
    et=data['demands'][from_node]
    return et

demand_callback_index = routing.RegisterTransitCallback(demand_callback)

routing.AddDimensionWithVehicleCapacity(

```

```

        demand_callback_index,
        0, # null capacity slack
        data['vehicle_capacities'], # vehicle maximum capacities
        True, # start cumul to zero
        'Capacity')

def battery_callback(from_index, to_index):
    """Returns the demand of the node."""
    from_node = manager.IndexToNode(from_index)
    to_node = manager.IndexToNode(to_index)
    m = pred_const[vehicle_id][from_node]
    distance = data['distance_real'][from_node][to_node]
    val = 1000
    pred = -m * distance * val
    return int(pred)

battery_callback_index =
routing.RegisterTransitCallback(battery_callback)

routing.AddDimensionWithVehicleCapacity(
    battery_callback_index,
    0, # null capacity slack
    [capacity * 1 for capacity in data['vehicle_battery_capacities']], #
vehicle maximum capacities
    True, # start cumul to zero
    'Battery')

battery_dimension = routing.GetDimensionOrDie('Battery')

# Define Transportation Requests.
for request in data["pickups_deliveries"]:
    pickup_index = manager.NodeToIndex(request[0])
    delivery_index = manager.NodeToIndex(request[1])
    routing.AddPickupAndDelivery(pickup_index, delivery_index)
    routing.solver().Add(
        routing.VehicleVar(pickup_index) ==
routing.VehicleVar(delivery_index)
    )

# Setting first solution heuristic.
search_parameters = pywrapcp.DefaultRoutingSearchParameters()
search_parameters.first_solution_strategy =
(routing_enums_pb2.FirstSolutionStrategy.PATH_CHEAPEST_ARC)
search_parameters.local_search_metaheuristic =
(routing_enums_pb2.LocalSearchMetaheuristic.GUIDED_LOCAL_SEARCH)
search_parameters.time_limit.seconds = 150

# Solve the problem.
solution = routing.SolveWithParameters(search_parameters)

# Print solution on console.
if solution:
    print_solution(data, manager, routing, solution, ecc_models,
vehicle_ids)
    print(data['distance_matrix'])
    print(data['distance_real'])

```

```

        vehicle_model_assignments = [ecc_models[i]['assistance_level'] for i
in range(num_vehicles)]

        plotter = PlotRoutes(solution, manager, routing, depot_location,
vehicle_model_assignments, data['distance_real'], customers_df)

        title = "E-ECCRP-1 - Optimization Scenario 1 - Babboe" # Define your
custom title here
        plotter.plot(title=title)

def print_solution(data, manager, routing, solution, ecc_models,
vehicle_ids):
    """Prints solution on console."""
    print(f"Objective: {solution.ObjectiveValue()}")
    total_distance = 0
    for vehicle_id in range(data["num_vehicles"]):
        index = routing.Start(vehicle_id)
        vehicle_id_key = vehicle_ids[vehicle_id] # Get the correct vehicle
ID key from the list
        vehicle_model = ecc_models[vehicle_id_key]['model']
        plan_output = f"Route for vehicle {vehicle_id} ({vehicle_model}):\n"

        route_distance = 0
        t_deliv = 0 # Initialize total deliveries for the vehicle
        t_pickups = 0 # Initialize total pickups for the vehicle
        cumulative_demand = 0 # Initialize cumulative demand
        max_cumulative_demand = 0

        # Assuming each vehicle's initial SOC is stored in
data['vehicle_battery_capacities'][vehicle_id]
        initial_soc = data['vehicle_battery_capacities'][vehicle_id]
        y1 = [initial_soc] # Initialize list to hold cumulative y_2 values

        previous_node = -1

        while not routing.IsEnd(index):
            node_index = manager.IndexToNode(index)
            if node_index != previous_node: # Add node if it's different
from the previous one
                plan_output += f" {node_index} ->"
                previous_node = node_index

            previous_index = index
            index = solution.Value(routing.NextVar(index))

            if not routing.IsEnd(index):
                distance =
data['distance_real'][manager.IndexToNode(previous_index)][manager.IndexToNode(index)]
                route_distance += distance
                t_pickups +=
data["demands_pic"][vehicle_id_key][manager.IndexToNode(index)]
                t_deliv +=
data["demands_del"][vehicle_id_key][manager.IndexToNode(index)]

                # Update cumulative demand and check if it's the maximum
cumulative_demand +=

```

```

(data["demands_pic"][vehicle_id_key][manager.IndexToNode(index)] +
data["demands_del"][vehicle_id_key][manager.IndexToNode(index)])
    max_cumulative_demand = max(max_cumulative_demand,
abs(cumulative_demand))

    m =
data['pred_const'][vehicle_id_key][manager.IndexToNode(index)]
    y2 = y1[-1] + m * distance * 1000
    y1.append(y2)

    plan_output = plan_output.rstrip('->') + f" -> 0"
    plan_output += f"\nTotal distance: {route_distance:.2f}km\n" + \
        f"Total delivered: {t_pickups} kg, Max load:
{max_cumulative_demand} kg\n" + \
        f"SoC: [{', '.join(f'{x:.2f}' for x in y1)}]\n"

    print(plan_output)
    total_distance += route_distance

    print(f"Total distance of all routes: {total_distance}km")

if __name__ == "__main__":
    main()

```

E-ECCRP-2

```

"""Enhanced Electric Cargo Cycle Routing Problem with 2 Batteries (E-ECCRP-2)"""
import pandas as pd
import json
from Random Forest (RF) import RandomForestModel
from ortools.constraint_solver import routing_enums_pb2
from ortools.constraint_solver import pywrapcp

def create_data_model(distance_matrix, demands, vehicle_capacities,
vehicle_battery_capacities, num_vehicles, demands_del_per_vehicle,
demands_pic_per_vehicle, pred_const, sequence_per_vehicle, extra_per_vehicle,
initial_soc, max_dist, pickups_deliveries, distance_real):

    """Stores the data for the problem."""
    data = {}
    data['distance_matrix'] = distance_matrix
    data['demands'] = demands
    data['vehicle_capacities'] = vehicle_capacities
    data['vehicle_battery_capacities'] = vehicle_battery_capacities
    data['num_vehicles'] = num_vehicles
    data['depot'] = 0
    data['demands_del'] = demands_del_per_vehicle
    data['demands_pic'] = demands_pic_per_vehicle
    data['pred_const'] = pred_const
    data['sequence'] = sequence_per_vehicle
    data['extra'] = extra_per_vehicle
    data['initial_soc'] = initial_soc
    data['max_dist'] = max_dist

```

```

data['pickups_deliveries']=pickups_deliveries
data['distance_real']=distance_real

return data

def main():
    """Entry point of the program."""

    # Instantiate the data problem.
    distance_matrix_file_path = 'path/distance_matrix.json'

    # Load customer data
    customer_data = 'path/service_points.xlsx'
    customers_df = pd.read_excel(customer_data)

    # Load ECCs information
    ecc_file_path = 'path/vehicle_list.xlsx'
    df_ecc = pd.read_excel(ecc_file_path)

    # Extract ecc_models information along with initial_soc and additional
    data for feature vector
    ecc_models = {}
    for index, row in df_ecc.iterrows():
        if row['availability'] == 'yes':
            ecc_models[row['vehicle_id']] = {
                'load_capacity': row['load_capacity'],
                'driver_weight': row['driver_weight'],
                'ecc_weight': row['ecc_weight'],
                'assistance_level': row['assistance_level'],
                'max_dist': row['max_dist'],
                'initial_soc': row['initial_soc'],
                'model': row['model']
            }

    vehicle_ids = list(ecc_models.keys())

    # Depot Location
    depot_location = (43.774076, -79.501122)

    # Load the distance matrix from the JSON file
    def build_rounded_distance_matrix(distance_matrix_file_path):
        # Load the distance matrix from the JSON file
        with open(distance_matrix_file_path, 'r') as f:
            distance_matrix1 = json.load(f)

        distance_matrix = []
        for row in distance_matrix1:
            rounded_row = [round(distance) for distance in row]
            distance_matrix.append(rounded_row)

        return distance_matrix

    distance_matrix =
    build_rounded_distance_matrix(distance_matrix_file_path)

    with open(distance_matrix_file_path, 'r') as f:
        distance_matrix2 = json.load(f)

```

```

    distance_real = [[float(round(distance,2)) for distance in row] for row
in distance_matrix2]

    pickups_deliveries = [[1, 16], [2, 17], [3, 18], [4, 19], [5, 20], [6,
21], [7, 22], [8, 23], [9, 24], [10, 25], [11, 26], [12, 27], [13, 28], [14,
29], [15, 30]]

    demands = [-row['demand'] if row['service'] == 'delivery' else
row['demand'] for index, row in customers_df.iterrows()]
    demands.insert(0, 0) # Insert 0 at the beginning for the depot

    vehicle_capacities = [model['load_capacity'] for model in
ecc_models.values()]
    vehicle_battery_capacities = [model['initial_soc'] for model in
ecc_models.values()]
    num_vehicles = len(ecc_models)
    initial_soc = [model['initial_soc'] for model in ecc_models.values()]
    max_dist = [model['max_dist'] for model in ecc_models.values()]

    rf_models = {}
    pred_const = {}
    model_paths = {
        'Ami': 'path/data - Ami.xlsx',
        'Babboe': 'path/data - Babboe.xlsx',
    }

    demands_del_per_vehicle = {}
    demands_pic_per_vehicle = {}
    sequence_per_vehicle = {}
    extra_per_vehicle = {}

    for vehicle_id, model_info in ecc_models.items():

        demands_del = [-row['demand'] if row['service'] == 'delivery' else 0
for _, row in customers_df.iterrows()]
        demands_del.insert(0, 0) # Insert 0 at the beginning for the depot

        demands_pic = [0 if row['service'] == 'delivery' else row['demand']
for _, row in customers_df.iterrows()]
        demands_pic.insert(0, 0)

        extra = [p + d for p, d in zip(demands_pic, demands_del)]
        extra2 = extra[1:]

        sequence = [0]
        # Loop through extra2 to calculate subsequent elements in the
sequence for each vehicle
        for value in extra2:
            sequence.append(sequence[-1] + value)

        # Store the calculated lists in the dictionaries
        demands_del_per_vehicle[vehicle_id] = demands_del
        demands_pic_per_vehicle[vehicle_id] = demands_pic
        extra_per_vehicle[vehicle_id] = extra
        sequence_per_vehicle[vehicle_id] = sequence

```

```

        model_type = model_info['model']

        ecc = [[model['ecc_weight'] for model in ecc_models.values()][0]] *
len(sequence)
        driver = [[model['driver_weight'] for model in
ecc_models.values()][0]] * len(sequence)
        total_weight = [e + r + d for e, r, d in zip(sequence, ecc, driver)]
        assistance = [[model['assistance_level'] for model in
ecc_models.values()][0]] * len(sequence)

        # Check if the model type is recognized and set parameters
accordingly
        if model_type == 'Ami':
            rf_model_path = model_paths['Ami']
            n_estimators = 200
            max_depth = 10
        elif model_type == 'Babboe':
            rf_model_path = model_paths['Babboe']
            n_estimators = 200
            max_depth = 5
        else:
            # Fallback or default values
            print(f"Warning: Model type {model_type} not recognized. Please
check.")
            continue # Skip this iteration

        # Create the RandomForestModel instance with the determined path
rf_model = RandomForestModel(rf_model_path)

        # Train the model with the determined parameters
rf_model.train_model(n_estimators=n_estimators, max_depth=max_depth)

        # Store the trained model in the dictionary with vehicle_id as key
rf_models[vehicle_id] = rf_model

        # Prepare the features for prediction
X_feature = pd.DataFrame({
    'Extra_Weight_kg': sequence,
    'Total_Weight_kg': total_weight,
    'Assistance_Level': assistance
})

        # Predict using the trained model and store the predictions
pred_const[vehicle_id] = rf_model.predict(X_feature)

        # Modify the data creation to include this new list
data = create_data_model(distance_matrix, demands, vehicle_capacities,
vehicle_battery_capacities, num_vehicles, demands_del_per_vehicle,
demands_pic_per_vehicle,
                        pred_const, sequence_per_vehicle, extra_per_vehicle,
initial_soc, max_dist, pickups_deliveries, distance_real)

        # Create the routing index manager.
manager = pywrapcp.RoutingIndexManager(
    len(data["distance_matrix"]), data["num_vehicles"], data["depot"]
)

```

```

# Create Routing Model.
routing = pywrapcp.RoutingModel(manager)

# Define cost of each arc.
def distance_callback(from_index, to_index):
    """Returns the manhattan distance between the two nodes."""
    # Convert from routing variable Index to distance matrix NodeIndex.
    from_node = manager.IndexToNode(from_index)
    to_node = manager.IndexToNode(to_index)
    return data["distance_matrix"][from_node][to_node]

transit_callback_index =
routing.RegisterTransitCallback(distance_callback)
routing.SetArcCostEvaluatorOfAllVehicles(transit_callback_index)

# Add Capacity constraint.
def demand_callback(from_index, to_index):
    """Returns the demand of the node."""
    from_node = manager.IndexToNode(from_index)
    to_node = manager.IndexToNode(to_index)
    et=data['demands'][from_node]
    return et

demand_callback_index = routing.RegisterTransitCallback(demand_callback)

routing.AddDimensionWithVehicleCapacity(
    demand_callback_index,
    0, # null capacity slack
    data['vehicle_capacities'], # vehicle maximum capacities
    True, # start cumul to zero
    'Capacity')

def battery_callback(from_index, to_index):
    """Returns the demand of the node."""
    from_node = manager.IndexToNode(from_index)
    to_node = manager.IndexToNode(to_index)
    m = pred_const[vehicle_id][from_node]
    distance = data['distance_real'][from_node][to_node]
    val = 1000
    pred = -m * distance * val
    return int(pred)

battery_callback_index =
routing.RegisterTransitCallback(battery_callback)

routing.AddDimensionWithVehicleCapacity(
    battery_callback_index,
    0, # null capacity slack
    [capacity * 2 for capacity in data['vehicle_battery_capacities']], #
vehicle maximum capacities
    True, # start cumul to zero
    'Battery')

battery_dimension = routing.GetDimensionOrDie('Battery')

# Define Transportation Requests.
for request in data["pickups_deliveries"]:

```

```

        pickup_index = manager.NodeToIndex(request[0])
        delivery_index = manager.NodeToIndex(request[1])
        routing.AddPickupAndDelivery(pickup_index, delivery_index)
        routing.solver().Add(
            routing.VehicleVar(pickup_index) ==
routing.VehicleVar(delivery_index)
        )

    # Setting first solution heuristic.
    search_parameters = pywrapcp.DefaultRoutingSearchParameters()
    search_parameters.first_solution_strategy =
(routing_enums_pb2.FirstSolutionStrategy.PATH_CHEAPEST_ARC)
    search_parameters.local_search_metaheuristic =
(routing_enums_pb2.LocalSearchMetaheuristic.GUIDED_LOCAL_SEARCH)
    search_parameters.time_limit.seconds = 150

    # Solve the problem.
    solution = routing.SolveWithParameters(search_parameters)

    # Print solution on console.
    if solution:
        print_solution(data, manager, routing, solution, ecc_models,
vehicle_ids)
        print(data['distance_matrix'])
        print(data['distance_real'])

        vehicle_model_assignments = [ecc_models[i]['assistance_level'] for i
in range(num_vehicles)]

        plotter = PlotRoutes(solution, manager, routing, depot_location,
vehicle_model_assignments, data['distance_real'], customers_df)

        title = "E-ECCRP-2 - Optimization Scenario 3 - Ami" # Define your
custom title here
        plotter.plot(title=title)

def print_solution(data, manager, routing, solution, ecc_models,
vehicle_ids):
    """Prints solution on console."""
    print(f"Objective: {solution.ObjectiveValue()}")
    total_distance = 0
    for vehicle_id in range(data["num_vehicles"]):
        index = routing.Start(vehicle_id)
        vehicle_id_key = vehicle_ids[vehicle_id] # Get the correct vehicle
ID key from the list
        vehicle_model = ecc_models[vehicle_id_key]['model']
        plan_output = f"Route for vehicle {vehicle_id} ({vehicle_model}):\n"
        route_distance = 0
        t_deliv = 0 # Initialize total deliveries for the vehicle
        t_pickups = 0 # Initialize total pickups for the vehicle
        cumulative_demand = 0 # Initialize cumulative demand
        max_cumulative_demand = 0

        # Assuming each vehicle's initial SOC is stored in
data['vehicle_battery_capacities'][vehicle_id]
        initial_soc = data['vehicle_battery_capacities'][vehicle_id]
        y1 = [initial_soc] # Initialize list to hold cumulative y_2 values

```

```

previous_node = -1

while not routing.IsEnd(index):
    node_index = manager.IndexToNode(index)
    if node_index != previous_node: # Add node if it's different
from the previous one
        plan_output += f" {node_index} ->"
        previous_node = node_index

    previous_index = index
    index = solution.Value(routing.NextVar(index))
    #route_distance += routing.GetArcCostForVehicle(previous_index,
index, vehicle_id)

    if not routing.IsEnd(index):
        distance =
data['distance_real'][manager.IndexToNode(previous_index)][manager.IndexToNode(index)]
        route_distance += distance
        t_pickups +=
data["demands_pic"][vehicle_id_key][manager.IndexToNode(index)]
        t_deliveries +=
data["demands_del"][vehicle_id_key][manager.IndexToNode(index)]

        # Update cumulative demand and check if it's the maximum
        cumulative_demand +=
(data["demands_pic"][vehicle_id_key][manager.IndexToNode(index)] +
data["demands_del"][vehicle_id_key][manager.IndexToNode(index)])
        max_cumulative_demand = max(max_cumulative_demand,
abs(cumulative_demand))

        m =
data['pred_const'][vehicle_id_key][manager.IndexToNode(index)]
        y2 = y1[-1] + m * distance * 1000
        y1.append(y2)

    plan_output = plan_output.rstrip('->') + f" -> 0"
    plan_output += f"\nTotal distance: {route_distance:.2f}km\n" + \
        f"Total delivered: {t_pickups} kg, Max load:
{max_cumulative_demand} kg\n"+ \
        f"SoC: [{', '.join(f'{x:.2f}' for x in y1)}]\n"

    print(plan_output)
    total_distance += route_distance

print(f"Total distance of all routes: {total_distance}km")

if __name__ == "__main__":
    main()

```